VISUALIZED DECISION MAKING: DEVELOPMENT AND APPLICATION OF INFORMATION VISUALIZATION TECHNIQUES TO IMPROVE DECISION QUALITY OF NURSING HOME CHOICE

A Dissertation
Presented to
The Academic Faculty

by

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In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
School of Industrial and Systems Engineering

Georgia Institute of Technology
August 2008

VISUALIZED DECISION MAKING: DEVELOPMENT AND APPLICATION OF INFORMATION VISUALIZATION TECHNIQUES TO IMPROVE DECISION QUALITY OF NURSING HOME CHOICE

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To all caregivers

ACKNOWLEDGEMENTS

This dissertation research is made possible in part through a GVU Seed Grant 2006-2007. The grant was designed to promote collaboration between different academic units at the Georgia Institute of Technology.

The author would also like to recognize the invaluable expertise and contribution of the dissertation committee (Drs. John T. Stasko, Mary Czerwinski, Stephen E. Cross, Gregory Abowd, and Brani Vidakovic) to this research. Their guidance has been extremely helpful and greatly appreciated.

In addition, I wish to thank Kevin Moloney, Erin Kinzel, Young Sang Choi, Miles Wei, Dr. Paula Edwards, and Mahima Ashok for their assistance and suggestions during the formation of the experimental protocol, the development of the proposed tool, the collection and analysis of data, and the completion of this document.

Another appreciation should be directed to over two hundred participants who shared their bitter experience and brilliant insights regarding nursing home choice. Especially, many caregiver groups including Alzheimer's Association, ElderCare Online™, My Care Community, Children of Aging Parents, ElderCare Rights Alliance, and National Family Caregivers Association, and their arduous members have provided not only insightful feedback and warm support.

For the last but not the least, the author would like to appreciate the unlimited support from my parents, Joo Ho Yi and Jong Sun Kim, and my sister, Yuna Lee. Especially, this dissertation would not be completed without the love and support of my fiancée, Stacy Soo-yeon Kim.

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SUMMARY

An individual's decision to place a close family member in a nursing home is both difficult and crucial. To assist consumers with such a decision, several initiatives have led to the creation of public websites designed to communicate quality indicators for nursing homes. However, a majority of consumers fail to fully utilize this information for various reasons, such as the multidimensionality, complexity, and uncertainty of the information. Some of the difficulties may be alleviated by information visualization (InfoVis) techniques. However, several unsuccessful attempts in applying InfoVis to decision making suggest that a thorough understanding of the user's perspective is necessary.

Accordingly, the author has developed an InfoVis tool for the decision domain of choice of a nursing home. First, a framework of overarching InfoVis and decision theories, called the "visualized decision making (VDM)" framework, has been developed and contextualized within the selection of a nursing home. Second, a decision-support tool using several InfoVis techniques such as the weighting slider bar and the distribution view have been designed for application within the framework, and the designed tool, called "VDM," was implemented. Third, VDM was empirically tested through a web-based experiment and follow-up interviews.

The results of this study showed that individuals faced with the decision of selecting a nursing home could make fairly high quality decisions when they used VDM. Though the effects of proposed InfoVis techniques were not evident, this study provided the theoretical framework and empirical results which may help other designers of

InfoVis techniques because this work addresses several issues consumers face when choosing a nursing home that can be generalized to other decision making contexts.

CHAPTER 1: INTRODUCTION

1.1 Motivation

According to consumer-decision-making literature, the more access to information consumers have, the better choices they make. This claim is not only intuitively true but also supported by several studies (e.g., Lancaster 1990; Payne, Bettman et al. 1993; Simonson 1999), which typically explain it by the following underlying rationale: 1) more alternatives to choose from increase the probability of finding the ideal alternative; and 2) more alternatives also lead to the development of a stronger preference structure because they allow decision makers to be flexible (Chernev 2003).

Fortunately, the need for access to more information has been satisfied. Due to the explosive growth of information and communication technologies, consumers in the most developed countries have the information at their fingertips. Worldwide, the Internet attracts one billion Internet users (Computer Industry Almanac Inc. 2006), who account for 86.3 billion USD in e-commerce sales in the United States alone (Scheleur, King et al. 2005). Today, consumers who want more information can collect an extraordinary amount of information through the Internet. For example, a prospective car buyer can access information about more than 300 car models, including detailed descriptions containing over 50 attributes (Consumers Union of U.S. Incorporation 2005).

However, the flipside to such easy access to information is the overwhelming nature of this resource. Too much information often degrades the quality of decision making. This phenomenon, often called “information overload,” has been reported in various fields, including accounting, business, marketing, and healthcare (e.g., Buchanan and Kock 2000; Eppler and Mengis 2004; Hall and Walton 2004). Iyengar and Lepper (2000) provided empirical evidence showing that a large set of choices (alternatives) has adverse consequences. That is, increasing the size of the decision set can decreases the likelihood of choosing the optimal alternative. Lee and Lee (2004) also empirically showed that information overload made online consumers less satisfied, less confident, and more confused.

Another clear example of a decision context in which this phenomenon of information overload is likely to occur is in the selection of a nursing home. In the United States, there were 15,989 nursing facilities that collectively have 1,743,059 beds as of 2005 (The American Health Care Association 2006). Demographic trends indicate rapid growth in the proportion of the population that is 85 years and older, which will soon necessitate a corresponding increase in the number of nursing homes or nursing care facilities (Quadagno and Stahl 2003). Thus, information overload due to the large number of nursing homes while one selects a nursing home will increase accordingly.

As a solution to these types of problems, information visualization (InfoVis) tools have recently emerged. Meyer predicted, “By means of visualization, […] perhaps, the problems of information overload will be overcome” (1998, p.207). Numerous sources, including a series of books by Edward Tufte (1983; 1990; 1997), have shown that numerous and complex data can be surprisingly easy to understand if presented using a proper visualization. Actually, several InfoVis techniques that claim to be helpful in decision making have been developed (e.g., Zhang 1996; Andrienko and Andrienko 2003; Carenini and Loyd 2004). In addition, some theoretical frameworks that combine the two separate areas of InfoVis and decision making (e.g., Bautista and Carenini 2006) have been proposed.

What is missing is a more comprehensive, empirical assessment of the effectiveness of visualization for decision making (Mirel 1998). The application of InfoVis to decision making has not been seriously or comprehensively considered despite the obvious needs and clear application areas (Kellen 2005). More structured empirical work is necessary to lay a sound foundation between InfoVis and decision making, especially in the domain of healthcare, in which many significant decisions are made.

1.2 Overview

Thus, the overarching goal of this thesis is to empirically show that InfoVis techniques improve decision quality especially when a decision maker suffers from the excessive amount of information. Since this single study cannot cover all possible decision making contexts and numerous InfoVis techniques, the boundary of the problem is detailed and specified as the author proceeds with the project.

The dissertation consists of the following seven chapters: 1) Chapter 1: Introduction; 2) Chapter 2: Literature Review; 3) Chapter 3: Requirements Analysis; 4) Chapter 4: VDM development; 5) Chapter 5: Usage Study; 6) Chapter 6: Follow-up Interviews; and 7) Chapter 7: Summary, Contributions, and Future Work.

More specifically, each chapter contains following contents: Chapter 2 presents an extensive literature review of InfoVis and decision science, which lays a sound theoretical foundation. As a result of the literature review, the Visualized Decision Making (VDM) framework is proposed. Chapter 3 presents user requirements collected through interviewing people who had prior experience in choosing a nursing home or anticipated choosing one in the near future. Chapter 4 describes how VDM was designed, evaluated, and implemented. Chapter 5 presents the procedure and results of a web-based experiment that tested VDM. Chapter 6 contains the results of additional follow-up interviews. Chapter 7 summarizes the entire dissertation and discusses the contributions and future work of this study.

The following formal statement succinctly summarizes the purpose of this study:

> *In the decision-making scenario of nursing home choice, the quality of decisions made with the assistance of designed InfoVis techniques is better than that made without those techniques present, and the differences between the two groups enlarge as the amount of data considered increases.*

Though the statement summarizes the overarching goal of this study, in order to achieve the goal, the following research questions should be answered:

- What are the influences of the large amount of data on decision quality?
- What are available InfoVis techniques that would help decision making?
- How to select a proper set of InfoVis techniques?
- What are the influences of InfoVis techniques on decision quality?
- How well do people without prior InfoVis knowledge embrace these techniques?

1.3 Anticipated Outcomes

This dissertation is an explorative, yet empirical study designed to assess the applicability of InfoVis techniques to aid decision making in an information-rich environment, namely the context of nursing home choice. Visualized information is intuitively helpful for a decision maker trying to understand the overall trends of patterns in data and to make better decisions (Kellen 2005). However, this proposition has not yet been rigorously tested. A review of the relevant literature reveals a dearth of empirical evidence. Thus, the research outcome of this dissertation may contribute to following areas.

The first contribution would be to propose a theoretical framework that combines two separate fields: decision science and InfoVis. Fortunately, Bautista and Carenini (2006) proposed an integrated task-based framework to design InfoVis for preferential choices. Their study serves as a basis for this work. However, since every decision involves a variable set of relevant or meaningful factors, this study will incorporate interviews with individuals who have experience choosing a nursing home for a close family member. The results of these qualitative studies will be used to verify and refine the framework.

The second contribution of this dissertation would be to design InfoVis techniques and an empirical test of their effectiveness within the context of nursing home choice. Since testing every possible InfoVis technique is impossible, an exemplar InfoVis application will be designed based on the constructed theoretical framework. While the exemplar application is empirically tested, the focus will be placed on not only testing the effectiveness of the overall InfoVis system but also explaining how the sub-InfoVis techniques affect the participants' cognitive procedures during decision making tasks. The author believes that identifying the underlying mechanisms for how InfoVis techniques affect cognitive procedures in users will provide a more helpful tool for other researchers and developers who are studying the decision making process.

The third and boldest contribution would be to provide design guidelines for the use of InfoVis techniques for decision support. These guidelines will be based on the findings of previous research as well as empirical studies proposed for this dissertation. While the guidelines will be limited contextually to nursing home choice, it is believed that these recommendations can serve as a basis for other researchers to build upon.

A related, fourth contribution would be to explore the potential for novel InfoVis techniques (e.g., methods of visually representing and/or interacting with multivariate data) that may emerge from the iterative design process of developing the exemplar InfoVis system. The effectiveness of any new techniques will be investigated through empirical testing while the major aims of this study are being pursued.

CHAPTER 2: LITERATURE REVIEW

User-centered design (Norman and Draper 1986; Vredenburg, Ji-Ye et al. 2002) strongly emphasizes the process or goal of understanding users when designing tools or systems. With respect to this work, the users are represented by individuals faced with the decision of selecting a nursing home. More specifically, information about who the decision makers are, what the main challenges are, and what matters to them, can be found in previously conducted survey studies. For example, Castle (2003) reported findings from 306 resident and 306 family member interviews pertaining to factors influencing their nursing home choices. The findings help to explain the decision making problem and the target population.

However, the studies have revealed very little about the cognitive processes consumers follow when deciding on a nursing home. To understand such processes, one can consult decision science. Since the selection of a nursing home is a representative decision making context, theories of decision making, particularly those of consumer decision making, can provide a wider and more comprehensive view of decision-making procedures. Among the innumerable studies conducted and theories developed, adaptive consumer decision making (Payne, Bettman et al. 1993) and information overload (Eppler and Mengis 2004) are particularly helpful to describe the procedures commonly involved with human decision making.

Other important information comes from research in the field of InfoVis. Though the history of InfoVis is relatively short, InfoVis researchers have conducted empirical studies on the use and effectiveness of numerous visualization techniques, resulting in continuously evolving taxonomies of InfoVis (Chi 2000; Qin, Zhou et al. 2003; Tory and Möller 2004; Amar, Eagan et al. 2005). This chapter reviews many of these techniques including multidimensional visualization techniques (Grinstein, Trutschl et al. 2001), interaction techniques (Yi, Kang et al. 2007) and uncertainty visualization (Pang, Wittenbrink et al. 1997; Zuk and Carpendale 2006).

Another important clue that can shed light on this issue is the link between decision science and InfoVis. Vessey's seminal work in cognitive-fit theory helped to identify the relationships between the presentation of information (i.e., tables vs. graphs) and cognitive tasks using the information (i.e., semantic and spatial tasks), which supported the link with empirical data (Vessey 1991; Vessey 1994). This work is still relevant today (Vessey 2006). In addition, Bautista and Carenini's (2006) task-based framework is helpful despite a relative lack of empirical evidence to prove the validity of this framework.

This chapter consists of four different sections: 1) Section 2.1 consists of a review of the relevant literature regarding the decision making context, namely the selection of nursing homes; 2) Section 2.2 consists of a review of decision theories and models that can be applied to help explain the nursing home decision; 3) Section 2.3 provides a comprehensive review of InfoVis taxonomies and techniques; and 4) Section 2.4 consists of several theories helpful in combining the domains of decision science and InfoVis.

2.1 Nursing Home

2.1.1 Overview

Nursing homes (or skilled nursing facilities, nursing care facilities) are the providers of long-term care for primarily the elderly population in the United States

(Sainfort, Ramsay et al. 1994). The large "baby-boomer" generation is aging, leading to a dramatic increase in the proportion of the U.S. population that is 85 years and older (Quadagno and Stahl 2003). These epidemiological changes will correspondingly intensify the need for the development and funding of new long-term care facilities. In April 2005, the United States had 15,989 nursing facilities housing and 1,435,761 individuals (The American Health Care Association 2006). The average age of nursing home residents is 85, with more women (74%) than men (26%). It is estimated that 46.2% suffer some form of dementia, 17% have a spouse, and some have neither family nor friends (Institute of Medicine 2001). Thus, for the majority of these individuals, the nursing home is truly the home environment and primary (or only) care provider.

Because 83% of nursing home residents suffer from multiple chronic diseases, and most are unable to eat, bathe, dress, move, or go to the bathroom without assistance (Institute of Medicine 2001), an insufficient level of quality of care in nursing homes could easily result in critical consequences to residents. Of greater concern is the enormous variation in quality among nursing homes, which has been reported in the past three decades. Thus, deciding which nursing home to enter (or which nursing home to place a loved one in) and monitoring the quality of a nursing home have become extremely important activities (Harrington, O'Meara et al. 2003).

Unfortunately, assessing the quality of a nursing home is difficult for an average consumer, as the quality is determined by not only directly observable and familiar characteristics such as cleanliness and location but also more specific metrics such as staffing, procedures, accident rates, and areas of specialty care, which should be observed longitudinally. Rather than a consumer's attempting to locate and understand all of this information, another approach is for federal or state government agencies to collect quality information about nursing homes, and then to systematically and publicly disseminate this information to consumers. This idea of publicly distributing quality information on healthcare facilities, including doctor’s offices, hospitals, and nursing homes, has been implemented within the past few decades. This publicly available quality rating of healthcare facilities has become commonly known as a “Report Card.”

2.1.2 Quality Indicators and Report Cards

Many studies on nursing home quality for the Report Cards have adopted the Donabedian model (1980), which ties together measures of structure, process, and outcome. Structural measures, which include metrics such as size, location, and occupancy rate, cover a provider’s ability to deliver care. Process measures, such as deficiency and complaints, are concerned with the services provided and the means by which they are delivered. Finally, outcome measures, including clinical quality indicators, refer to the residents’ physical and mental health conditions resulting from the care provided (Sainfort, Ramsay et al. 1995; Harrington, O'Meara et al. 2003). In addition, Rantz and colleagues (1999) appended the Donabedian model with more measures representative of consumer and provider perspectives. Based on the results of eleven focus groups, they formed an integrated multidimensional model of quality of nursing home care, which contained the following categories: home, staff, care, environment, communication, and family involvement.

Based on these models, multiple forms of quality information on nursing homes are publicly available. The information with the widest geographical coverage is perhaps the NHC website (http://www.medicare.gov/NHCompare), created by Center for

Medicare and Medicaid Services (CMS) in 1999 (see the president's announcement in U.S. Department of Health and Human Services, 1998). The NHC website contains the quality information on Medicare or Medicaid certified nursing homes. On September 3, 2006, a total of 15,934 nursing homes were registered in the NHC database (Centers for Medicare and Medicaid Services 1999). (A detailed list of the number of nursing homes in each state is available in Appendix A.) As this website regularly hosts about 100,000 visitors a month, this information is clearly in demand (U.S. House of Representatives: Committee on Government Reform 2002).

The NHC website provides the following information for each nursing home in the database:

- Overview (10 measures)
    - Location
    - Distance from the given zip code
    - Medicare participation (Yes / No)
    - Medicaid participation (Yes / No)
    - Initial date of certification
    - The total number of beds
    - Type of ownership (non-profit corporation / for profit corporation)
    - Whether it is located in a hospital (Yes / No)
    - Multi-home (chain) ownership (Yes / No)
    - Resident and family councils (Resident / family / both)
- Quality Measures (15 measures)
    - For long-stay residents

        - Percentage of residents whose need for help with daily activities has increased (0 -100%)
        - Percentage of residents who have moderate to severe pain (0-100%)
        - Percentage of high-risk residents who have pressure sores (0-100%)
        - Percentage of low-risk residents who have pressure sores (0-100%)
        - Percentage of residents who were physically restrained (0-100%)
        - Percentage of residents who are more depressed or anxious (0-100%)
        - Percentage of low-risk residents who lose control of their bowels or bladder (0-100%)
        - Percentage of residents who have/had a catheter inserted and left in their bladder (0-100%)
        - Percentage of residents who spend most of their time in bed or in a chair (0-100%)
        - Percentage of residents whose ability to move about in and around their room got worse (0-100%)
        - Percentage of residents with a urinary tract infection (0-100%)
        - Percentage of residents who lose too much weight (0-100%)
    - For short-stay residents
        - Percentage of short-stay residents with delirium (0-100%)
        - Percentage of short-stay residents who had moderate to severe pain (0-100%)
        - Percentage of short-stay residents with pressure sores (0-100%)
- Inspection (4 measures for each deficiency)
    - The number of deficiencies

        - Descriptions of deficiencies
        - Affected residents (Few/some/many)
        - Level of harm (1: Potential for minimal harm / 2: Minimal harm or potential for actual harm / 3: Actual harm / 4: Immediate Jeopardy)
        - Date of correction
- Staff (4 measures)
    - Licensed nursing staff hours per resident per day
        - Registered nurses hours per resident per day (hours and minutes)
        - Licensed practical nurses/licensed vocational nurses hours (hours and minutes)
    - Certified nursing assistant hours per resident per day (hours and minutes)
    - Total number of residents

Some of the measures are presented with averages for the United States and the participating state in which the nursing home is located. This information could be used as a benchmark for judging and comparing the relative quality of a nursing home or interest. Furthermore, a detailed description for each indicator is given in order to help an individual who does not possess prior knowledge or a basic understanding of the indicators regarding nursing homes. The contents of the NHC website mainly come from two data sources such as the Online Survey, Certification, and Reporting (OSCAR) database and the Minimum Data Set (MDS) Repository. The OSCAR database contains information about "the nursing home characteristics and health deficiencies issued during the three most recent State inspections and recent complaint investigations." The MDS

Repository contains information on “the resident's health, physical functioning, mental status, and general well-being” (Centers for Medicare and Medicaid Services 1999).

State governments also provide nursing home decision makers with quality information. Castle and Lowe (2005) identified 19 states (AZ, CO, FL, IL, IN, IO, MD, MA, MS, NV, NJ, NY, OH, PA, RI, TX, UT, VT, and WI) that provide nursing home report cards based on their survey during the period of January through March 2003. However, the amount and structure of presented information differ substantially from state to state. For example, the Arizona report card has only one quality and eight background data elements, while the Ohio report card has 34 quality and 33 background data elements. Eleven states use numerical scales (e.g., number of deficiencies and percentage satisfied) in their report cards while four states use “Consumer Reports-style” rating systems. Only five states provide more detailed textual information rather than numeric or categorical scoring scales (Castle and Lowe 2005).

In spite of this variation among the states, using the NHC website as a primary reference for currently available nursing home quality information would be a wise starting point for individuals faced with the decision of selecting a nursing home. Even though the representations differ among the states, the primary source of information is the MDS Repository, which is also a primary source of information for the NHC website. Only a few states (OH and VT) use different quality measures (e.g., satisfaction of residents or family members) compared with the other data sources. Given these trends, the present study and its theoretical grounding were based on the 33 background and quality measures from the NHC website.

2.1.3 Challenges in Selecting a Nursing Home

Even though many initiatives, including CMS, provide publicly available quality information on nursing homes, whether the availability of this quality information on nursing homes actually helps decision makers remains questionable. For example, Robinson and Brodie (1997) found that only 34% of consumers with access to report card information actually used it. Actually, only a few studies have examined the potential influence of nursing home report cards on consumer choices (e.g., GAO 2002; Harrington, O'Meara et al. 2003; Mukamel and Spector 2003; Castle and Lowe 2005). However, these studies have generally agreed that although the information is clearly useful, enhancing the usability of quality information for nursing home consumers is a great challenge.

Among the most salient problems with the use of the nursing home quality indicators is that the quality indicators themselves do not represent simple and straightforward information. Researchers have mentioned three challenging aspects of such indicators. First, the definitions of quality are not simple, as they are multidimensional concepts. After all, many aspects of a nursing facility contributing to the construct of quality differ from attributes that would describe quality in hospitals or emergency care settings. This form of long-term care is less dependent on high-tech instruments and highly-trained physicians and staff, but rather more heavily on unskilled and/or informally educated care-givers. In addition, nursing facilities serve as a (largely) permanent residence, so social living considerations that impact quality of care or life must also be made. As Sainfort et al. (1995) point out, “Nursing facility care requires that the functional, medical, social and psychological needs of residents be individually determined and met by careful assessment and care planning" (p.64).

Another challenging aspect of the indicators is that prior knowledge of the nursing healthcare domain is required for a thorough understanding each quality indicator. Understanding terms such as "delirium" and "pressure sores" and assessing the implication of the data is challenging to the average individual faced with deciphering which factors are important to their selection of a nursing home. Moreover, some quality indicators require risk adjustment, increasing the complexity of this problem. The risk adjustments are necessary since some residents by nature (i.e., due to genetics, lifestyle choices, or prognosis) are more likely to develop detrimental health conditions. In this case, the presence of such conditions is not necessarily the fault of the facility providing care. Risk factors associated with each quality indicator have been analyzed to account for these clinical issues (Arling, Karon et al. 1997). However, depending on the risk adjustment methods, the resulting quality indicators can carry different values, which could be even more confusing to a consumer who refers to multiple sources of quality information.

The quality indicators can also pose another challenge: inherent uncertainty within the quality indicators or the data used to generate the values of the indicators. Even though the stability of measures over time and across surveyors suggests that many quality indicators are reasonable measures of nursing home quality (Karon, Sainfort et al. 1999), some quality indicator data for nursing homes may often be missing because they are incomplete or inaccurate due to mistakes made during the survey procedures (GAO 2002) or too small number of residents. An individual who must process a large amount of information in a short amount of time while selecting a nursing home may overlook or misinterpret missing pieces of information. Thus, despite the critical nature of such a decision, the individual may make a suboptimal decision.

In addition to aspects of the information itself and access to that information, additional sources of complexity in decision making can be associated with the selection of a nursing home. For example, the individual faced with the task of choosing a nursing home is often a family member rather than a prospective resident (Castle 2003), rendering the decision making process more complex, as two sets of preferences and values need to be resolved. Several other characteristics of the average decision maker may also create challenges. For one, an individual's prior domain knowledge of nursing care or nursing home facilities is likely very limited. Each year, more than 800,000 people become first-time nursing home residents (Spence and Wiener 1990), which suggests that they or their family members may be new to this decision. For most people, the selection of a nursing home, for themselves or a loved one, is not likely to be a routine task. Besides this initial decision, they must also take on additional work. For example, after admission to a nursing home, some family members and friends may monitor any changes in the quality (of care) of the particular nursing home. In this case, the individual(s) monitoring the nursing home may (or may not) need more in-depth knowledge of some of the quality indicators that they may not possess.

Second, as alluded to earlier, individual decision makers are just that—individuals. As such, different consumers have unique preference structures. For example, potential residents who have diabetes or who are bed-bound are likely to place more emphasis on quality indicators regarding expertise in diabetes and diet management or skin care and prevention of pressure ulcers. In contrast, family members of residents with dementia are likely to have more concerns regarding expertise in the care and management of those with cognitive impairment (Mukamel and Spector 2003). Thus, it may also be difficult for users to glean which quality indicators are of particular personal importance if the data are too abstract to be linked to specific conditions.

Third, the choice of a nursing home is often made under extreme time pressure. That is, relative to the importance of the decision, the "…choice of nursing home is most often made within a few days of hospitalization of the elder" (Castle 2003, p.51). This time constraint limits the number of nursing homes (i.e., alternatives) that the decision maker can actually visit and/or investigate. Because of this limitation, the information provided in the report cards becomes extremely important. In the absence of word-of-mouth recommendations from friends and/or family members, report cards might be the only official, comparative information that the average decision maker can rely on (McAuley, Travis et al. 1997; Castle and Lowe 2005).

All of these challenges are quite intertwined, and thus complicated. Although several researchers have proposed solutions to this problem, few (e.g., Hibbard and Peters 2003) have extended this decision making problem to other potentially helpful research domains such as decision science and InfoVis, the information from which, the author believes, can be applied to either alleviate some of the problems or generate possible solutions to them. To fill this gap, in the following sections, the literature from both decision science and InfoVis is reviewed within the context of the nursing home selection.

2.2 Decision Making

2.2.1 Overview

A decision implies "an irrevocable choice of an action that has value-relevant consequences" (Edwards and Fasolo 2001, p.582). Since a decision is irrevocable and may also often have critical consequences, decision making has received considerable attention by researchers (Edwards and Fasolo 2001). Due to its ubiquitous nature, decision making has also been investigated by many researchers in various domains, including economics, management, cognitive science, psychology, and operations research, among others.

Intuitively, decision making can be perceived as a very rational, analytical, and even mathematical procedure. In fact, until the mid 1990's, it was the dominant perspective shared among numerous economists, statisticians, and philosophers. During this period, decision models generally assumed that a human decision maker is an "economic man" who represents the ideal, rational decision maker (Edwards 1954). Representative theories of this normative view of decision making are the subjective expected utility theory and decision models with multiple objectives and attributes. In these theories and models, the static and invariant preference structure of a decision maker was assumed to be known or derivable. The derived preference structures are used to evaluate each option or alternative (often mathematically), leading to the selection or identification of an optimal choice or choices (Keeney and Raiffa 1993).

However, this notion was harshly criticized by some behavioral-focused decision scientists, such as Herbert Simon (1955), who argued that humans are frequently found to make sub-optimal and irrational decisions in real situations, a phenomenon resulting from their limited cognitive capacity, especially when it is combined with environmental complexity. In the 1990's, this idea of an imperfect decision maker was expanded and organized into behavioral decision research (BDR) (Payne, Bettman et al. 1992). According to researchers in this descriptive view of decision making, decision makers are often limited in their information processing abilities due to their limited cognitive capacity, more commonly referred to as "bounded rationality." Many other studies (e.g., Payne, Bettman et al. 1992; Slovic 1995; Bettman, Luce et al. 1998; Fischhoff, Welch et al. 1999) have found that decision makers' preference structures are variant and constructive, compared with what normative decision theorists had previously believed. In this view, decision makers are not always immediately knowledgeable about the nature of a decision making problem that determines their preference for an alternative; instead, they have a set of "fuzzy" goals they wish to accomplish. Thus, their preferences may shift as they discover a preference structure that may better meet their objectives (Slovic 1995).

Research into these two schools of thought (i.e., normative and descriptive theories) fundamentally involves different approaches. Normative decision scientists basically ask "how should a person make a decision?" In contrast, descriptive decision scientists ask "how does a person actually make a decision?" Edwards and Fasolo (2001) also argued that normative theories are just special cases of subsets of descriptive theories of decision making, given that they represent (perhaps) the mathematically optimal way in which a person might make a decision. However, taking either the normative or descriptive approach to an extreme is problematic. For example, we can observe how people make decisions, but simply following what one or several people do in a decision situation does not guarantee that one will make the best, or at least better, decision (Cohen, March et al. 1972). In contrast, while normative theories of decision making may involve rigorous and mathematical procedures in the decision making process, they are often too cumbersome to be realistically or practically applied by a human being faced in a real decision making context.

As is often the case in life, the ideal approach would be a balance between two approaches, that is, answering the question “What people should and can do?” This balanced school of thought is referred to as “prescriptive decision making.” While the prescriptive approach is nothing new, the normative and descriptive approaches disagree, and the gap between the two seems to be widening (Luce and von Winterfeldt 1994). Thus, a proper approach should be to narrow the gap between the two different theoretical mindsets.

2.2.2 Decision Making Model and Strategies

Providing an exhaustive review of decision making theories is simply not feasible (Lehto and Nah 2006). However, to provide the proper tools to aid a decision maker, concrete information about the kinds of support decision makers need is crucial. For this purpose, this section will review decision theory and modeling and the strategies human decision makers often use. However, this discussion will remain fairly general, as the support that a decision maker needs can vary widely, depending on the decision context. For example, the information a mutual fund investor would want to know would be very different from the information a car buyer might want and/or need. The former might want to know the average return on and estimated risk of an investment, which would require primarily numerical data. The latter, however, might want to know not only the price of a car but also subjective qualities such as the “feel” of a car or its aesthetic value, which is not typically translated into numerical data. When the nature of the decision making problem differs, the means by which users can be supported may also change.

Thus, in this section, decision making theories will be discussed based on two primary questions: 1) What steps should a decision maker follow? (e.g., the decision making procedure); and 2) What kinds of problems will a decision maker encounter? (e.g., common problems in the decision making procedure). In their response to these two questions, normative and descriptive views often differ, so both perspectives will be discussed and compared. Moreover, this discussion will also include other factors that influence decision making and measurable outcomes, the purpose of which will be to design a pertinent experiment.

2.2.2.1 Normative Approaches

Herbert Simon (1977) roughly described the steps of managerial decision making as 1) the intelligence activity, 2) the design activity, 3) the choice activity, and 4) the review activity. The term for the first activity is borrowed from the military meaning of intelligence. Although Simon intended the four steps for managerial decision making, the steps, detailed in Table 1, are non-specific, so they can be applied to other decision making situations.

Table 1. Four-phase managerial decision making (adapted from Simon 1977)

Phases	**Description**	**Time spent**
Intelligence activity	Surveying environments to identify new conditions that require actions.	Larger/longer
Design activity	Designing alternative actions in order to deal with the new conditions.	Even larger/longer
Choice activity	Choosing one action from among the alternatives to deal with problems based on analysis of the consequences of the choices.	Smaller/shorter
Review activity	Reviewing the outcomes of the choices	Moderate

A more elaborate view of the steps involved in the activities is shown in Table 2. These nineteen steps of a decision making procedure are quite comprehensive and use the underlying foundations of three primary decision theories: multi-attribute utility (MAU), maximum subjectively expected utility (Max SEU), and Bayes' theorem of probability theory (Bayes) (Edwards and Fasolo 2001). The three different theories are based on the core tenets of the normative approach.

Table 2. Nineteen steps to a decision (adapted from Edwards and Fasolo 2001)

Step	Task
1	Identify the options.
2	Identify the possible outcomes associated with each option.
3	Identify the attributes with which to evaluate these outcomes.
4	Score each outcome on the basis of each attribute.
5	Weigh the attributes for relative meaning or important.
6	Aggregate the scores and weights into utilities (MAU).
7	Identify the events that determine which of the outcomes will follow the selection of an option.
8	For each event, specify a prior distribution of probability.
9	Identify information that might modify the probabilities specified in step 8.
10	If the information is free or cheap, buy it (Max SEU)
11	If the information has an associated cost, find out how much.
12	Determine the conditional gain from the purchase of the information.
13	Aggregate the cost of information and gain from having it (Max SEU).
14	Decide whether to buy the information (Max SEU + Bayes).
15	If the information is purchased, update the prior probabilities accordingly (Bayes).
16	Return to Step 11. Iterate the process until no new information is purchased (Max SEU).
17	Assemble the output (numbers) from steps 6 and 15.
18	Calculate the expected utilities (Max SEU).
19	Choose the option with the highest expected utility (Max SEU).

Note. MAU, multi-attribute utility; Max SEU, maximum subjectively expected utility; Bayes, Bayes' theorem of probability theory.

Primarily, multi-attribute utility (MAU) theory pertains to the evaluation of outcomes. One of the most important concepts in decision science is "utility," or the subjective value. Utility, which is the value(s) perceived by a decision maker, differs from the actual value of a choice. For example, $100 to an impoverished person is likely to have a relative value, or utility, exceeding the same $100 to an extremely wealthy person. However, utility depends on differences not only among individuals but also within any one individual, depending on the aspects of the situation, including the various attributes of the decision context.

For example, if a person has four job offers, as shown in Table 3, given the choice of Company A or Company B, the person may choose Company B because it allows employees to sacrifice one week of vacation time to earn an additional $10,000 a year, particularly since $50,000 is not enough to take a long vacation. However, when the same person is given the choices of Company C or Company D, the person might prefer Company C to Company D, as an $100,000 is a already sufficient salary. The additional $10,000 may not provide the same value as an extra week of vacation. This example shows that the same amount ($10,000) can have different exchange values: sometimes it is more valuable than one week of vacation, but sometimes it is not. Thus, the preference structure cannot be easily modeled with a simple weighted average model in this case.

Table 3. Annual salaries and vacations of four job offers

	Annual Salary ($)	Vacation (weeks)
Company A	50,000	3
Company B	60,000	2
Company C	100,000	2
Company D	110,000	1

Thus, the MAU of a certain option (i.e., job offer) can be described in Equation 1, in which $v(X_{j1}, X_{j2}, X_{j3,} \cdots, X_{jK})$ is the utility of choice X_j. Note that every attribute of X_j is considered to evaluate its utility.

$$MAU(X_j) = v(X_{j1}, X_{j2}, X_{j3,} \cdots, X_{jK}) . \tag{1}$$

Bayesian theory is about the assessment of probabilities. In real settings, decisions are often made under uncertain conditions, but sometimes, the attributes of each choice cannot provide the decision maker with complete information about each choice or alternative. In addition, each choice can generate different outcomes due to uncertainty. The assessment of uncertainty can be adjusted according to the prior experiences of and other sources of information available to the decision maker. To incorporate this additional information to resolve some of this uncertainty, one must use Bayesian theory.

MAU and Bayesian theory can be combined using SEU. When the two methods of decision modeling are combined, an approximation is often used, and since evaluating an aggregated utility function is too cumbersome, the weighted average of the single-attribute utilities is also often used. This simplification ignores the interaction effects between the attributes, such as those discussed in the salary and vacation example. While the simple weighted additive model does not work in some cases (Keeney and Raiffa 1993), a lack of value interaction among attributes is considered to be a sign that the attributes have been properly selected or modeled (Keeney 1992). The following equation describes SEU:

$$\mathrm{SEU}(Xj) = \sum_{k=1}^{K} [w_k u_k (X_j)]. \tag{2}$$

In Equation 2, $u_k(X_j)$ is the single-dimensional expected utility of choice X_j on the *k*th attribute, and w_k is the weight of *k*th attribute. Note that utility (v) (see Equation 1) and expected utility (u) have different notations. After the SEU for all *J* options has been calculated, an option that maximizes the SEU will be selected (corresponding to step 19 in Table 2). From Table 2, one can easily imagine that following these 19 steps without omission would be very cumbersome even though some steps are indicated as optional (e.g., steps 10, 11, and 15). Such challenges stem from not only having multiple steps but also the following aspects of each process.

First, evaluating a utility function itself is a challenging task, especially when a decision maker does not have sufficient knowledge or experience regarding the decision making problem. Assessing the utility of a certain attribute could be challenging because the decision maker may not envision the consequence of making a certain choice. Prospect theory also describes how perceived values can be affected by how information is framed or presented (Kahneman and Tversky 1979).

Evaluating a utility function with considerable information (e.g., numerous attributes or alternatives) can also be a cumbersome activity that could lead to information overload (Buchanan and Kock 2000). As shown in Equations 1 and 2, as the number of attributes and choices increase, the amount of processing required increases drastically. In our nursing home choice problem, adding an alternative (i.e., another nursing home) or attribute (i.e., another quality indicator) substantially increases the processing requirements. For example, if there are 100 alternatives and 30 attributes, adding one choice or attribute increases the number of processes required (30 and 100, respectively), to obtain a corresponding utility function, even when the simple weighted average is assumed. Thus, this characteristic of the SEU method can result in a cognitive burden on a decision maker.

Another problem in modeling human decision making, according to Slovic and others (Payne, Bettman et al. 1992; Slovic 1995; Bettman, Luce et al. 1998), is the often instable and malleable nature of the values or preferences of a human decision maker. In other words, the weights (w_k) or utilities ($u_k(X_j)$) assigned by the decision maker, which are often not permanently determined, change during the process of decision making. This idea, called “constructive preference structure,” has received intense attention from decision scientists. The tendency for constructive preference by human decision makers causes major difficulties for many normative decision theories because they are based on the assumption of preference invariance.

Another difficulty lies in the assessment of probability, which is subject to various biases by the decision maker. Actually, many of the natural biases made by decision makers are related to an incorrect assessment of probability (see Appendix B for details). Such a biased perception of probabilities has been well described by Wilinson (2005, p.466), who states, "Human decision making in the face of uncertainty is not only prone to error, it is also biased against Bayesian principles. We are not randomly suboptimal in our decisions. We are systematically suboptimal. Numerous studies of decision making now make it clear that the mistakes novices and experts make are due mainly to innate biases." (p. 466).

The problems in decision making are not only limited to the issues described above. Many other internal and external factors such as variability in decision styles, searching preferences, belief systems, task complexity, and time pressure also affect decision making (Scott and Bruce 1995). All of these factors severely complicate models pertaining to decision makers and decision-making strategies. To complicate the matter, the conflicts among the multiple stakeholders in shared decision making causes totally different sets of problems (Kerr, MacCoun et al. 1996). Sometimes, a particular group of people may make biased decisions (Gladwell 2005), in which case multiple stake holders' interests are compromised and have to be adjusted. In addition, communication among multiple decision makers and organizational dynamics contribute to even more complications.

However, among all of these problems, information overload is playing increasingly larger role. As more and more information becomes available and accessible to a decision maker via the Internet and information technologies, a decision maker's cognitive capability to deal with all this information is limited and remains relatively unchanged, a situation that occurs during all complex decision making problems, including choosing a nursing home. This limitation, referred to as "bounded-rationality," was well described by Simon (Simon 1955) a half century ago, but 50 years of additional research has not produced any definitive solutions to this problem.

One solution for information overload might be an automated machine that handles the complexity instead of a human. With respect to mathematics and processing power, a computerized system is much more adept at solving complex equations. However, this solution of automated decision making, based on the optimization of a model (such as those described in Equations 1 and 2), may not be entirely successful mostly due to the issue of constructive preference structures. In other words, even though human decision makers struggle with excessive information, they are also the only ones that can actively generate and resolve evolving preference structures. If the preference structure is not known in advance, the human decision maker must be kept in the loop during the decision making process. Thus, in the end, automation without human decision makers might not be a sufficient solution to information overload.

Another problem particularly salient in the context of the nursing home choice problem is the uncertainty involved in decision making. As discussed in Section 2.1, much of the information provided in the quality measures of nursing homes is probabilistic, missing, and/or difficult to interpret. Without proper treatment of uncertain data, decision making will be inherently error-prone. Therefore, mitigation of this uncertainty by some means is necessary if a decision maker is to make an informed choice.

These three problems—information overload, constructive preference structure, and uncertainty—will not simply disappear because of incremental advances in the technology available to human decision makers. The crux of the problem is that these issues are human-centric. Thus, the resolution of these problems will not occur by replacing humans in the decision making process, but rather by supporting them with directed (technological) aid that can expand their abilities and strengthen the inherent weaknesses of human cognition.

2.2.2.2 Descriptive Approaches

Typically, one cannot make a decision by considering all relevant information, as it will inevitably cause information overload. As such, the decision maker must use short-cuts that reduce the complexity of the problem. Innumerable decision-making short-cuts, or strategies, exist. Researchers have even built a taxonomy of such strategies (Wright 1975; Bettman, Luce et al. 1998). According to the taxonomy of Wright, strategies are organized along two dimensions: "data combination processes" and "choice rules." Data combination processes have two levels, compensatory and non-compensatory data integration. In compensatory data integration, a good value of one attribute compensates for a bad value of another attribute, so all attributes are considered at the same time. By contrast, non-compensatory data integration could drop a choice with a bad value of an attribute, even if the choice or alternative has perfect values for the other attributes (Edwards and Fasolo 2001). The other dimension, choice rule, also has two levels: "best" and "cut-off." The best choice rule chooses the best option through heuristics (e.g., choosing an alternative that has the highest number of good features and the smallest number of bad features), whereas the cut-off rule merely eliminates available options based on a decision maker's threshold (e.g., eliminating alternatives that have bad aspects that do not meet criteria until only a few alternatives remain).

Table 4 outlines these strategies and heuristics. The distinction among levels in the two dimensions will be clarified when each decision strategy is discussed. In Table 4, three heuristics (WADD, EQW, and VOTE) are categorized in both the best and cut-off rules since the calculated score through these heuristics can be used as a cut-off criterion.

Payne et al. (1988) also introduced some combination of multiple strategies such as EBA+MCD, EBA+WADD, and EBA+EQW.

Table 4. Decision heuristics (adapted from Wright 1975; Bettman, Luce et al. 1998)

Choice rule	Data combination process	
	Compensatory	Non-compensatory
Best	WADD EQW VOTE MCD	LEX LEXSEMI MAXIMAX MINIMAX
Cut-off	WADD EQW VOTE	SAT EBA

Weighted Adding (WADD), Lexicographic (LEX), Lexicographic semi-order (LEXSEMI), Satisficing (SAT), Elimination-by-Aspects (EBA), Equal Weight (EQW), Majority of Confirming Dimensions (MCD), Feature Voting (VOTE), Maximize Minimum (MINIMAX), and Maximize Maximum (MAXIMAX)

In applying a weighted adding strategy (WADD), the subjective importance ratings are associated with each attribute. These subjective ratings, or weights, are multiplied by the corresponding attribute value obtained by a particular alternative. The worth of any particular alternative, then, would be the sum of these products (i.e., assigned weight by attribute value), and the decision maker selects the alternative with the greatest value. Equal Weight (EQW) is a special case of weighted adding. Since each attribute is considered equally important in this method, the value of each alternative is simply the sum of all its attribute values.

The strategy of feature voting (VOTE) is based on the number or frequency of occurrences of positive or negative features within an alternative. Here, the decision maker subjectively defines the positive and negative values for each attribute. The worth of the alternative is determined by the number of good votes (positive features) and bad votes (negative features). The decision maker may also disregard the number of bad votes or focus on minimizing the number of bad votes.

Paired comparisons are central to the strategy of majority of confirming dimensions (MCD). In this strategy, decision makers start by evaluating the first two alternatives. They then count the number of times each alternative has the higher score across all the attributes. The alternative with the higher count is then compared with the next alternative, and the process is repeated until all the alternatives have been considered. Finally, the alternative with the most "wins" is selected.

Another strategy, the lexicographic (LEX) decision rule, involves picking the alternative that has the highest value on the most important attribute. If multiple alternatives are equally good on the most important attribute, then the alternative that also has the greatest value on the second most important attribute is chosen. The lexicographic semi-order (LEXSEMI) method is a variation of LEX. In LEXSEMI, the condition of "equally good" is loosened by introducing the concept of "just-noticeable difference." For example, if car A is $20,000 and car B is $20,050 (but has better gas mileage), a car buyer using LEX will choose car A because car A is cheaper than car B. However, if another car buyer using LEXSEMI looks at gas mileage, which may be the second most important attribute, he may choose car B since $50 would become insignificant compared with future savings on gas costs.

The satisficing (SAT) method is a matter of selecting the first alternative that meets all the decision maker's requirements on the attributes. As such, decisions resulting from this technique depend on the order that the alternatives are presented.

Two similar non-compensatory decision strategies are minimize maximum loss (MINIMAX) and maximize maximum gains (MAXIMAX). A decision maker "applying MINIMAX compares the options on their worst attributes, rejecting one if another worst attributes is less offensive or if another has fewer worst attributes that are equally offensive. He minimizes maximum loss. MAXIMAX implies a consumer compares options on their best attribute, choosing one over another if its best attribute is more desirable or if it possesses more best attributes of equal desirability" (Wright 1975, p.61).

Finally, elimination-by-aspects (EBA) is a strategy of eliminating alternatives that have bad aspects that do not meet criteria until only a few alternatives remain. Often, the most important aspect (or attribute) is selected for inspection. If other alternatives have bad values for the attributes, they are eliminated from the candidates. For example, if one thinks that gas mileage is important, he can eliminate cars that have bad mileage, say less than 20 miles per gallon, from the pool of candidates.

Even though these strategies describe how people make decisions more accurately than the normative approaches, they also have some problems. For example, some non-compensatory methods mistakenly remove the optimal alternative(s). For example, if a decision maker uses EBA, and if the optimal alternative has a bad value for a certain attribute, the optimal alternative can be eliminated from the pool of candidates due to this particular bad attribute even though the overall utility may be better than that of the remaining alternatives. Even compensatory strategies pose difficulties for those seeking to make the optimal choice. For example, if one uses MCD, the choice can vary depending on the order of comparisons, as the decision maker may eliminate a good alternative merely because it takes a “loss” in an early comparison and may have won several other comparisons with the remaining alternative.

Contingent decision making describes the trade-off situations in more detail (Payne, Bettman et al. 1993). Payne and his colleagues measure the effort expended on and accuracy resulting from the application of different strategies. They assume that performing each strategy has associated costs in the form of small information processing tasks referred to as elementary information processes (EIPs). The number of EIPs for a decision strategy is assumed to be the measure of effort in making the decision. The accuracy of a strategy is measured in relative terms; “that is, the quality of the choice expected from a rule [strategy] is measured against the standard of accuracy provided by a normative model like the weighted additive rule [WADD]” (NOTE: Brackets have been added for terminology consistency) (Payne, Bettman et al. 1993, p.93).

As shown in Figure 1, use of the WADD method represents the most accurate, albeit most costly (in terms of effort) strategy to perform. In contrast, EBA is the most effortless strategy, but accuracy must often be sacrificed. Note that random choice is not considered here because it is not considered a method of decision making per se.

2.2.2.3 Prescriptive Approaches

As mentioned in the previous sections, the normative and descriptive approaches have their own advantages and disadvantages. The normative approaches may lead a decision maker to the optimal decision, but they often require more cognitive effort. In contrast, the decision strategies discussed in the descriptive approaches are more effortless, but decision outcomes are less accurate. From the perspective of prescriptive decision making, some error-prone decision strategies should be oppressed or restricted, and more accurate strategies should be more promoted as long as decision makers devote the required effort.

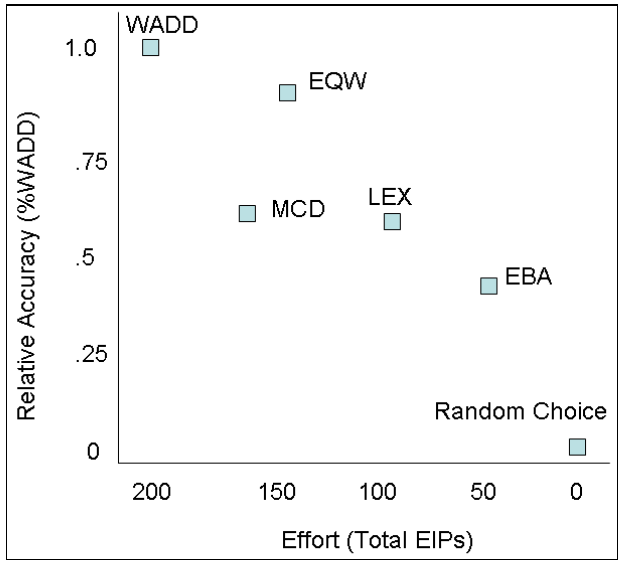

Figure 1. Tradeoff between relative accuracy and effort (adapted from Payne, Bettman et al. 1993)

The question then is how to help people make decisions more accurately and effortlessly. Todd and Benbasat (1991; 1993; 2000) conducted a series of empirical studies showing the effectiveness of computer-based decision aids. They showed that "when a more accurate normative strategy [WADD] is made less effortful to use, it is used" (NOTE: Brackets have been added for terminology consistency) (Todd and Benbasat 2000, p.91). This decision aid helps decision makers perform more accurate decision strategies with less effort. Another interesting result of the same study is that although the decision aid also provided features to support non-compensatory strategies (EBA), the non-compensatory strategies were not significantly promoted. Todd and Benbasat argued that the non-compensatory strategies are only preferred when support for the compensatory strategies is low. However, an alternative explanation would be that EBA was not used often because the data set used in the experiment was not large (ten apartments with eight attributes).

An experiment conducted by Speier and Morris (2003) shows another interesting piece of information. They compared a visual interface with a text-based interface. The results showed that decisions made using text-based interface were better when information overload was low, and decisions made using the visual interface were better when information overload was high. They even argued that "these visual interfaces appear to be less effective when specific details are needed or when there are a small number of data points" (Speier and Morris 2003, p.410). However, this argument cannot be generalized to other InfoVis techniques because the visual interface used in the experiment was a dynamic query (Shneiderman 1994) designed to support mainly the non-compensatory strategy (EBA). A more persuasive explanation would be as follows: 1) The dynamic query worked well under high information overload since it supported non-compensatory strategies effectively; or 2) the dynamic query worked rather poorly under low information overload since non-compensatory strategies were not needed. What they missed may be an InfoVis technique to support compensatory strategies.

However, supporting a compensatory strategy is cumbersome. According to Edwards and Fasolo (2001), who reviewed representative Web-based decision aids, compensatory strategies have been sparingly employed by Web-based decision aids since interfaces supporting compensatory strategies are complicated and difficult to use. Thus, providing proper decision aids that assist target users requires some additional design effort to minimize the required efforts. Some creative solutions, probably using InfoVis techniques, will be required.

Another lesson from reviewing these results is that information overload plays an important role in selecting proper decision strategies. Under high information overload, non-compensatory strategies such as EBA appear to be more effective since they filter out unnecessary information. After filtering is over, compensatory strategies or relatively normative approaches appear to be more effective since more comprehensive comparisons among the alternatives are necessary. Thus, a proposed decision aid should support both strategies effectively.

2.2.3 Factors Influencing Decision Making

Another difficulty for the study of behavioral patterns in decision making is that behaviors are often influenced by various other factors. Several factors that might confound the influence of potential independent variables include the following:

Time pressure. Hahn et al. (1992) empirically showed that information overload is typically not present if the decision maker is under no time pressure or restriction Given enough time, a decision maker is less susceptible to the effects of an overwhelming amount of information, allowing them to perform better as the amount of information increases. As discussed, however, individuals faced with selecting a nursing home are often under time pressure and thus likely to suffer from the negative impact on their ability to manage increasing amounts of information (e.g., many alternatives or several attributes or both). Furthermore, the effect of time pressure in this decision domain may also be significantly influenced by the emotional implications of the decision itself. Thus, to simulate reality, experiments must include the element of time pressure and emphasize the emotional consequences of such a decision.

Framing effects. Although logically equivalent, two separate wordings can be perceived differently depending on how they are framed or presented (Kahneman and Tversky 1979). For example, people may interpret or perceive a 5% failure rate and a 95% success rate differently even though they logically represent the same situation. This phenomenon can be an important factor in our decision context of nursing home selection since many of the quality indicators can be presented in either a positive or negative fashion. For example, the "Percent of Residents Who Have Moderate to Severe Pain (0 - 100%)" can be presented with an alternate, positive spin: "Percent of Residents Who Do Not Have Moderate to Severe Pain (0 -100%)." Negatively presented quality indicators were actually criticized since this framing is both counterintuitive and possibly confusing to consumers (GAO 2002). However, despite this criticism, the way in which quality indicators are presented in the NHC website has not changed (Centers for Medicare and Medicaid Services 1999).

Knowledge. The decision maker's level of background knowledge in the decision making domain (e.g., nursing care facilities) is another important aspect. For example, Agnew and Szykman (2005) found that the selection of investment options are strongly related to the (financial) background knowledge of the participant. In particular, low-knowledge individuals selected the default option more often than high-knowledge individuals, providing evidence for a status quo bias: simply selecting the option considered to be the "standard." As most individuals choosing nursing home have little prior knowledge about nursing homes and decision making criteria (Castle 2003), the level of knowledge should be assessed and controlled during the experiment.

Demographic factors. Certain demographic factors also affect the selection of the decision strategy to be used. For example, older adults have demonstrated a tendency to use non-compensatory strategies that reduce cognitive demands while younger adults tend to use compensatory strategies (Johnson 1990). Other demographic factors that affect searching include gender (Booske and Sainfort 1998; McDonald and Spencer 2000), and education level (Stavri 2001). In computer-based information searches, computer experience also effects one's search behavior (Mead, Sit et al. 2000) and efficiency due to its effect on the time required to complete basic computer tasks (Emery, Edwards et al. 2003). More specifically, in case of choosing nursing, demographic factors, such as ethnic groups (minority or not) and education levels, affect decision making as well (Angelelli, Grabowski et al. 2006).

2.2.4 Measures of Decision-Making Performance

Although a ubiquitous research topic in decision science (Edwards and Fasolo 2001), the measurement of the performance and quality of decision making continues to pose considerable challenges. Many different goals may exist in decision making, but the following consumer objectives have been listed by Bettman and colleagues (1998):

- Maximizing the accuracy of the choice
- Minimizing the cognitive effort required to make the choice
- Minimizing the experience of negative emotion when making the choice
- Maximizing the ease of justifying the decision.

Accuracy is relatively easy to measure as long as the preference structure of the decision maker is stable and elicited correctly. One method that Lee and Lee (2004) used was to include an artificial dominating alternative. Then, whichever preference structure that a participant possessed, the dominating alternative would be the most accurate choice. However, this use of an artificial alternative that represents the best choice can significantly lower the validity of the experiment. Another method of measuring accuracy is to collect the decision maker's preference structure before and after a task is performed and seeing whether a chosen alternative is the best one based on the collected preference structure. When collecting one's preference structure, the visual analog scale was often used (e.g., Stiggelbout 2000; Lenert, Sturley et al. 2002). Several decision scientists used choice quality as a measure of decision accuracy. Choice quality was a relative score of the weighted additive utility of a choice. For example, when the best option in terms of the weighted additive utility is chosen, the choice quality is 1.0. When the worst option is chosen, the choice quality is 0.0. The following equation shows how choice quality is calculated (Payne, Bettman et al. 1988; Lurie 2004):

$$\text{Choice quality} = \frac{WeightedAdditiveValue_{Choice} - WeightedAdditiveValue_{Worst}}{WeightedAdditiveValue_{Best} - WeightedAdditiveValue_{Worst}}$$

Agnew and Szykman provided overload and satisfaction measures in asset allocation tasks (Agnew and Szykman 2005). These questions can cover the second and third goals of Bettman and colleagues (listed above). These questions/measures are tested in their experiment and the questions can be modified to fit the context of the nursing home choice problem. This can be performed in the following way:

The following lists overload measures (on a scale of 1 to 6, from strongly disagree to strongly agree):

- There were too many different nursing homes to consider.
- This decision required a great deal of thought.
- This was a difficult decision.
- I found this decision to be overwhelming.
- It was difficult to comprehend all of the information available to me.
- This task was stressful.
- It was a relief to make a decision.

The following lists satisfaction measures:

- How satisfied are you with your choice? (Scale 1 to 7, Very Dissatisfied to Very Satisfied)
- How certain are you that you made the best choice? (Scale 1 to 7, Very Uncertain to Very Certain)
- How confused did you feel while performing the task? (Scale 1 to 7, Very Confused to Not at all Confused)
- How likely is it that you did not make the best choice? (Reverse scored, Scale 1 to 7, Very Unlikely to Very Likely)
- How likely is it that some of the choices that you did not choose would be equal to or better than the ones that you did choose? (Reverse scored, Scale 1 to 7, Very Unlikely to Very Likely)

Additional measures of cognitive overload would include the use of the NASA-TLX, as Speier and Morris (2003) did in their study. The NASA-TLX has six subscales related to human workload. Even though NASA-TLX has been used for a long time, this measure might be unfamiliar with our target users. Thus, NASA-TLX will be used as a supporting measure, if it is used at all.

The fourth goal – maximizing the ease of justifying the decision – is a little bit more difficult to measure quantitatively. The justification of a participant regarding their choice will be collected, and their confidence regarding their justification will be collected through Likert scale-based questions. In addition, the strategies or heuristics used in the experiment could reflect the cognitive processes used by the decision maker. The heuristics and strategies identified in the previous sections could be used and selection (or rejection) of the alternative that matched the particular strategy used by the decision maker could be used as a measure for justification of the option selection.

2.3 Information Visualization

One solution to these problems faced by decision makers or the designers of systems to support decision makers could be InfoVis. This recently emerged field of research is defined as "the use of computer-supported, interactive, visual representation of (abstract) data to amplify cognition" (Card, Card et al. 1999). Since InfoVis techniques exhaustively utilize the visual sensory channel, which has the biggest bandwidth among all possible sensory channels, the bounded-rationality problem may be alleviated or resolved. Furthermore, the interaction techniques heavily used in InfoVis techniques often engage users in the tasks, which might alleviate problems caused by an instable preference structure of the decision makers. The old axiom of "a picture is worth a thousand words" may also have some implications of how InfoVis can alleviate some information overload. The visual or graphical representation of data is often significantly easier and faster to process than textually-based representation of data.

However, all problems in decision making will not be solved by simply using InfoVis techniques; and not all InfoVis techniques are helpful for solving problems in decision making. As Vessey's classic study (1991; 1994; 2006) of cognitive-fit theory showed, neither tables nor graphs can support all the cognitive tasks. Some tasks (e.g., semantic tasks) are better performed using tables while other tasks (e.g., spatial tasks) are better performed using graphs. Thus, identifying the underlying cognitive tasks of decision making and applying the proper InfoVis techniques are the overall goals.

Unfortunately, researchers have devoted only limited effort in combining emerging knowledge from InfoVis with the accumulated knowledge of decision science. Even though most of InfoVis techniques are claimed to directly or indirectly support decision making, few studies (e.g., Bautista and Carenini 2006) have attempted to build a model or framework bridging the gap between the two fields. In particular, empirical studies, although urgently needed, are lacking (Mirel 1998).

In this section, currently available theoretical background of InfoVis, such as its potential and known benefits as well as its taxonomies will be reviewed. However, this theoretical background is not comprehensive enough to bridge the gap between InfoVis and decision science. Instead of listing all the possible design alternatives, some inspiring and thought-provoking InfoVis techniques considered relevant to the decision making process of selecting a nursing home will be reviewed and discussed in terms of how they can assist in some of the decision strategies previously discussed. The author believes that such a discussion will support informed brainstorming for a creative solution.

2.3.1 Theory of InfoVis

2.3.1.1 Models and Framework of InfoVis

InfoVis techniques have attracted many users over the past two decades, from basic consumers using popular websites to business workers using popular applications (Plaisant 2004). Tufte's three books are often cited as evidence of the efficacy of visualization techniques (Tufte 1983; Tufte 1990; Tufte 1997). Dull and Tegarden (1999) argue that the visualization of data can improve problem-solving capabilities, particularly when dealing with multidimensional data. Card and colleagues (1999) listed some benefits of visualization techniques:

- Increasing the memory and processing resources available to the user
- Reducing the search for information
- Using visual representations to enhance the detection of patterns
- Enabling perceptual inference operations
- Using perceptual attention mechanisms for monitoring
- Encoding information in a manipulable medium.

Thomas and Cook (2005, p.48) also list how InfoVis amplifies cognition as follows:

- Increased resources
    - High-bandwidth hierarchical interaction
    - Parallel perceptual processing
    - Offload work from cognitive to perceptual system
    - Expanded working memory

- Expanded storage of information
- Reduced Search
  - Locality of processing
  - High data density
  - Spatially-indexed addressing
- Enhanced recognition of patterns
  - Recognition instead of recall
  - Abstraction and aggregation
  - Visual schemata for organization
  - Value, relationship, and trend
- Perceptual inference
  - Visualization representations make some problems obvious
  - Graphical computations
- Perceptual monitoring
- Manipulable medium

These benefits are in line with the objective of aiding the targeted group of decision makers in their goal of selecting a nursing home. In order to lower the cognitive effort of users and to promote more accurate decision making strategies, increasing the resources available to users and enhancing their perceptual inference would be very beneficial. In addition, by providing a manipulable medium, a decision maker can interactively examine his decision and the various trade-offs of selecting alternatives.

However, the interaction between visualization and cognition are yet to be fully understood. Some procedural models have been proposed by Spence (2001) and Ware

(2000) although these procedural models appear to be insufficient to guide InfoVis designers to come up with appropriate and effective InfoVis techniques.

More recently, Amar and Stasko (2005) provided a framework that reveals two analytic gaps (i.e., the Worldview Gap and the Rationale Gap) between current visualization systems and more analytical systems. The Worldview Gap is defined as the gap between what the current visualization system shows and what actually needs to be shown to formulate relationships or make decisions. However, making a decision is often not the final stage, but the arrived-upon decision is often tested in terms of confidence and usefulness. It is here where the Rationale Gap exists. The Rational Gap is the gap between simply perceiving a relationship or making a decision and being able to explain and test the relationship or the decision. Amar and Stasko provided six recommendations: 1) determine the domain parameters, 2) expose the multivariate explanation, 3) facilitate hypothesis testing, 4) expose uncertainty, 5) concretize relationships, and 6) expose cause and effect. The first three recommendations are for bridging the Worldview Gap, and the other three are for bridging the Rational Gap.

Bautista and Carenini's (2006) Preferential choice Visualization Integrated Task (PVIT) model is yet another step forward regarding the combination of InfoVis and decision science. PVIT has two dimensions: decision steps, which include construction, inspection, and sensitivity analysis; and the relevance to the model or alternatives, which includes the attribute, the model, and the model + the attribute. They combined Sheneiderman's Task by the Data Type Taxonomy (TTT) (Shneiderman 1996), Amar & Stasko's knowledge tasks (Amar and Stasko 2005), Carenini and Loyd's basic cognitive tasks (Carenini and Loyd 2004), their own task analysis results, and tasks from Adaptive

Decision Making and Value-Focused Thinking into their framework (Payne, Bettman et al. 1993) and organized in the two-dimensional spaces. The 20 tasks that they identified are shown in Table 5.

Table 5. Tasks in the Preferential Choice Visualization Integrated Task (adapted from Bautista and Carenini 2006)

Tasks	Decision Steps [a]	Model/ Alternative [b]
1. Filter out uninteresting alternatives (list creation)	C	A
2. Addition/modification of each alternative at any point	C	A
3. Selection/marking of an alternative	C	M+A
4. Selection of objectives (hierarchy creation)	C	M
5. Definition of value function of each primitive objective	C	M
6. Determine initial objective weighting	C	M
7. Addition/modification of objectives at any point	C	M
8. Inspection of domain values of each alternative	I	A
9. Maintain an overview of all relevant information	I	M+A
10. For each alternative, assessment of the contribution to total value of each objective	I	M+A
11. Comparison of alternatives with respect to objective value	I	M+A
12. Assessment of the extent to which each objective weight contributes to total	I	M+A
13. Inspection of hierarchy of objectives	I	M
14. Represent/display missing data	I	M+A
15. Comparison of alternatives with respect to total value	I	M+A
16. Inspection of component value function	I	M
17. Inspection of range on which each primitive objective is defined	S	M
18. Comparison of results among different evaluations	S	M+A
19. Sensitivity analysis of changing a weight	S	M+A
20. Sensitivity analysis of changing a component value function	S	M+A

[a] Construction (C), inspection (I), and sensitivity analysis (S)
[b] Alternative (A), model (M), alternative and model (A+M)

Even though these task lists are very comprehensive, implementing features to support all 20 tasks might result in InfoVis techniques that are too complicated for decision makers to easily use and leverage. For example, tasks regarding a value function (i.e., 5, 16, and 20) are closely in line with the normative decision approaches. However, understanding the concept of value functions could be too challenging for target users. Moreover, the task model can provide comprehensive sets of cognitive tasks, but it does not provide any possible InfoVis techniques beyond linking to Sheneiderman's TTT, so the creation of InfoVis techniques still depends on the creativity of InfoVis designers or developers.

2.3.1.2 Taxonomies of InfoVis Techniques

In a rather general sense, Simon (1996) emphasized that developing a taxonomy is an early step to explaining a set of phenomena. According to some prior InfoVis studies, the goals of taxonomies are summarized as follows: 1) The taxonomy helps designers create a presentation that amplifies users' cognition; 2) it provides a common vocabulary for evaluating the efficacies of the InfoVis system; 3) it helps users identify which technologies that they might want to use to accomplish their tasks; and 4) it "…clarifies and interprets ideas and purposes behind techniques" (Qin, Zhou et al. 2003; Amar, Eagan et al. 2005).

In the context of the current study, the goal of creating a taxonomy is to provide design alternatives of InfoVis techniques to designers or at least to inspire designers through the application of some relevant InfoVis techniques. To accomplish this goal, the existing taxonomies are comprehensively reviewed. Some taxonomies (e.g., Leung and Apperley 1999; Griethe, Fuchs et al. 2005) that are too specific to apply to a particular technique are omitted unless they are relevant to our goal.

According to the definitions and framework of InfoVis, InfoVis techniques can be divided into four distinct components: data, presentation, interaction techniques, and cognitive activities. However, these distinctions are often vague and become confusing within a taxonomy. For example, Shneiderman's seven analytic tasks include zooming. However, zooming is closer to an interactive technique rather than a natural cognitive activity or task (Shneiderman 1996). However, many of the reviewed taxonomies, outlined in Tables 6, 7, 8, and 9, follow this four-element framework.

Table 6. Taxonomy according to data types

Publications	Taxonomy Items (examples)	Comments
(Bertin 1981)	Data value and data structure	N/A
(Stevens 1946)	Category data, integer data, and real-number data	Ware (2000) mentioned that this category is more practical
(Shneiderman 1996)	1D, 2D, 3D, time, mD, tree, and network	N/A
(OLIVE, 1997)	1D, 2D, 3D, time, mD, tree, network, workspace	Added the "workspace" type to Shneiderman's taxonomy (1996).
(Card, Card et al. 1999)	Physical data, 1D, 2D, 3D, mD, tree, and network.	This taxonomy is very similar in nature to Shneiderman's categories.
(Ware 2000)	Entities, relationships, and attributes (nominal/ordinal/interval/ratio or 1D, 2D, 3D, …)	Ware's category (e.g., entities and relationships) is based on Bertin's (1981) distinction between data value and data structure.
(Keim 2002)	1D (ThemeRiver), 2D (Polaris and MGV), mD (Polaris and Scalable Framework), text and hypertext (ThemeRiver), hierarchies and graphs (MGV and Scalable Framework), algorithms and software (Polaris)	N/A

Table 7. Taxonomy according to presentation types

Publications	Taxonomy Items (examples)	Comments
(Buja, Cook et al. 1996)	1D (histogram, density plots, cdf plots, Q-Q plots, jitter plots, box plots), time series (time series plot), 2D (perspective plot, level plots), and 3D/mD (Scatter plots, Traces, Glyphs)	N/A
(Keim and Kriegel, 1996)	Pixel-oriented techniques (spiral pixel-arrangement techniques), Geometric project techniques (scatter plot, parallel coordinates, etc.), Icon-based techniques (shape coding, color icons, Chernoff faces, stick figure, star glyphs, etc.), Hierarchical techniques (n-Vision, dimensional stacking, treemap, etc.), and Graph-based techniques (Hy+, Margritte, SeeNet, etc.)	N/A
(Keim 2002)	Geometrically transformed displays (scatter plot matrices, projection views, hyperslice, and parallel coordinates), iconic displays (Chernoff faces, MGV, star icons, stick figure icons, color icons, TileBars), dense pixel displays, and stacked displays	Keim called this "Visualization techniques."

Table 8. Taxonomy according to interaction

Publications	Taxonomy Items	Comments
(Shneiderman 1996)	Overview, zoom, filter, details-on-demand, relate, history, and extract	Even though these are named as “analytic tasks” by Shneiderman, these are closer to interaction techniques.
(Buja, Cook et al. 1996)	Focusing (choice of projection, aspect ratio, zoom, pan, choice of variable, order, scale, scale-aspect ratio, animation, 3-D rotation), linking (brushing as conditioning / sectioning / database query), and arranging views (scatter plot matrix and conditional plot)	These three techniques are corresponding to Buja’s three tasks (i.e., Finding Gestalts, Posing Queries, and Making comparisons). Additionally, Buja and colleagues pointed out different presentations induce different interaction techniques.
(Chuah and Roth 1996)	Input, output, operation	Basic visualization interaction (BVI).
(Keim 2002)	Dynamic projections, interactive filtering, interactive zooming, interactive distortion, interactive linking and brushing	N/A
(Wilkinson 2005)	Filtering (categorical/continuous/multiple/fast filtering), navigating (zooming/panning/lens), manipulating (node dragging/categorical reordering), brushing and linking (brush shapes/brush logic/fast brushing), animating (frame animation), rotating, transforming (specification/assembly/display/tap/tap tap/tap tap tap)	N/A

Table 9. Taxonomy according to cognitive activities

Publications	Taxonomy items	Comments
(Buja, Cook et al. 1996)	Finding Gestalts, Posing Queries, and Making comparisons	N/A
(Zhou and Feiner, 1998)	(See Table 10)	N/A
(Amar, Eagan et al. 2005)	Retrieve Value, Filter, Compute Derived Value, Find Extremum, Sort, Determine Range, Characterize Distribution, Find Anomalies, Cluster, Correlate	N/A
(Bautista and Carenini 2006)	(See Table 5)	N/A

Table 10. Zhou and Feiner's visual implications and related elemental tasks (adapted from Zhou and Feiner 1998)

Implication	Type	Subtype	Elemental tasks
Organization	Visual grouping	Proximity	Associate, cluster, and locate
		Similarity	Categorize, cluster, distinguish
		Continuity	Associate, locate, reveal
		Closure	Cluster, locate, outline
	Visual attention		Cluster, distinguish, emphasize, locate
	Visual sequence		Emphasize, identify, rank
	Visual composition		Associate, correlate, identify, reveal
Signaling	Structuring		Tabulate, plot, structure, portray, quantify
Transformation	Modification		Emphasize, generalize, reveal
	Transition		Switch

2.3.1.3 Sensemaking and InfoVis

Another important concept that gains increasing attention from current InfoVis researchers, especially who are interested in the evaluation of InfoVis techniques, is sensemaking. Since the term "sensemaking" is used in numerous contexts (e.g., organizational research, educational research, and decision science), definitions of sensemaking vary. However, one of elaborate definitions, by Klein et al. (2006), described sensemaking as "a motivated, continuous effort to understand connections (which can be among people, places, and events) in order to anticipate their trajectories and act effectively" (p.71). Certainly, choosing a nursing home using various, overwhelming information is sensemaking to understand how the quality information implies to his or her decision. It is also a motivated, continues effort.

The sensemaking procedure was well summarized by the Data/Frame Theory of sensemaking of Klein et al. (Klein, Moon et al. 2006). They argue that sensemaking involves two cycles: 1) elaborating a frame and 2) reframing as shown in Figure 2.

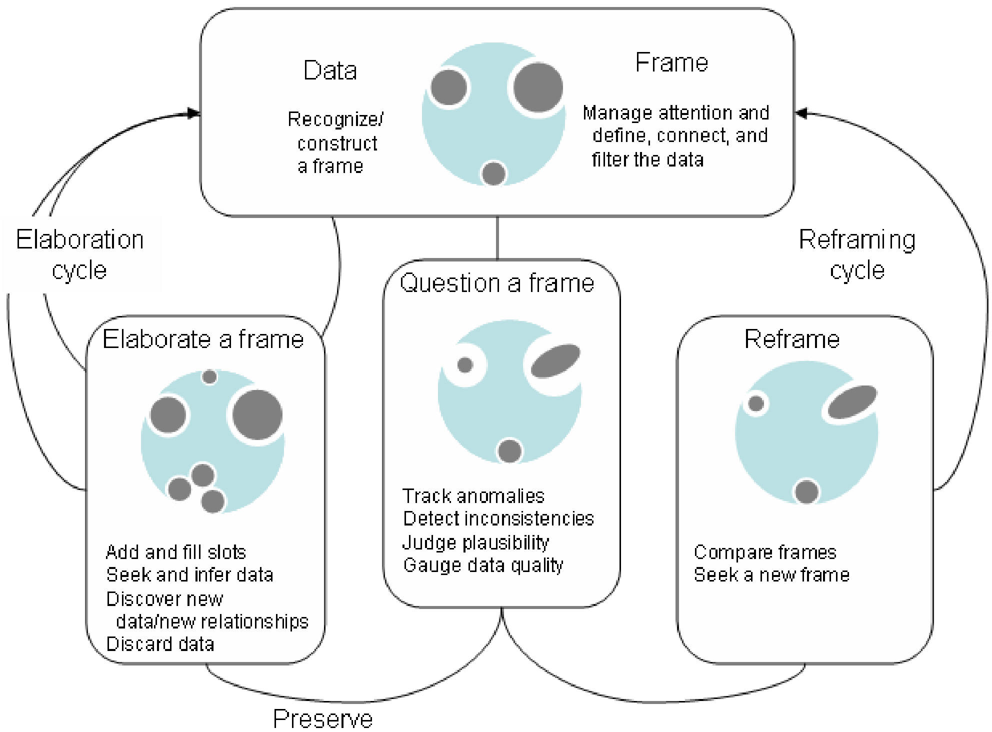

Figure 2. The data/frame theory of sensemaking (adapted from Klein, Moon et al. 2006)

The framework shows that sensemaking is not only an iterative procedure but also an interactive and creative procedure since one has to come up with frames to understand given data. Due to these characteristics of sensemaking, InfoVis tools and techniques could have great potentials to expedite sensemaking since the framework and data could be visually presented and interactively manipulated. This notion of the InfoVis tool as a supporting tool to make sense of data can be directly applicable to the present dissertation topic, choosing a nursing home. While choosing a nursing home, decision makers should make sense of data to understand what the available information means to their individual circumstances. They should formulate their own framework (e.g., the preference structure) to understand information. If some information does not make sense to them, they should adjust their framework (or preference structure). Sometimes, understanding some information might generate more questions. Then, they should investigate more to find more information.

Conversely, some insights found in the sensemaking literature should be carefully reviewed and borrowed while designing and evaluating an InfoVis tool. As summarized in Table 11, Klein et al. listed six myths in terms of sensemaking (Klein, Moon et al. 2006). These findings about sensemaking should be applied carefully considered to design InfoVis tools or techniques to promote sensemaking or decision making.

Table 11. The myths of sensemaking and corresponding findings (adapted from Klein, Moon et al. 2006)

Myths	Findings
"Data fusion and automated hypothesis generation aid sensemaking."	"Research shows that when human decision makers are put in the position of passively receiving interpretations, they're less apt to notice emergent problems." (p. 72)
"Sensemaking is simply connecting the dots."	It simplifies too much the cognitive process when analysts connect the dots. It appears to be a simple process, but determining which dots are important or not is a very crucial and cognitively intense task.
"More information leads to better sensemaking."	More information increases the performance up to a certain point, but too much information degrades performance. In addition, people can be over-confident with too much information.
"It's important to keep an open mind"	People who show the best performance is not the people who have open mind always, but the people who jumped into a conclusion initially and deliberately and continuously test it.
"Biases are inescapable and prevent reliable sensemaking"	"The so-called biases are mostly found in laboratory studies using artificial puzzle tasks and college freshmen as subjects, conditions that minimize expertise and context. In natural settings, biases can disappear or be greatly reduced." (p.72)
"Sensemaking follows the waterfall model of how data lead to understanding"	"Sensemaking doesn't always have clear beginning and ending points. The simplified waterfall model of cognition runs counter to empirical evidence about expert decision making, and it runs counter to evidence showing that data themselves must be constructed." (p.72)

2.3.2 Practices of InfoVis

In this section, some InfoVis techniques are reviewed as baseline designs. In addition, references are provided that serve as a motivation for improved InfoVis methods specifically designed to support decision making, specifically within the context of selecting a nursing home.

2.3.2.1 Multivariate InfoVis

Within the field of InfoVis, multivariate InfoVis is probably the most relevant visualization category to multi-attribute decision making. Multivariate InfoVis includes an array of techniques that essentially transform multidimensional data into visual representations on "real world displays." Many visualization techniques have been developed and identified from the taxonomy reviews, which include Principal Component Analysis (Hand, Mannila et al. 2001), Multidimensional Scaling (Cox and Cox 2001), Parallel Coordinates (Inselberg and Dimsdale 1990), Star Coordinates (Kandogan 2001), Chernoff's Face (Chernoff 1973), Star Plot (Chambers 1983), Scatter Plot Matrix (Hand, Mannila et al. 2001), Trellis plot (Cleveland 1993), Worlds within Worlds (Feiner and Beshers 1990), Table Lens (Pirolli and Rao 1996), and ValueCharts (Carenini and Loyd 2004; Bautista and Carenini 2006). While these particular techniques of visually representing multivariate data provide a solid foundation, much of the ongoing research pertains to the improvement of the quality of these methods.

However, one intrinsic problem with all of these methods is that correlations between different dimensions (or attributes) are severely distorted when multidimensional information is projected to a lower-dimensional (most likely two-dimensional) display, which is called the "curse of dimensionality reduction" (Bellman

1961). Such distortion may neither be intuitive nor easy for untrained users to interpret (Yi et al., 2005). However, identifying the relationships between multiple attributes might not be an important task from the perspective of the decision maker. It is likely that the more important or primary task of the decision maker is to compare the alternatives across their various attributes. Thus, some of the multivariate InfoVis techniques (e.g., scatter plot matrix) that focus on examining the relationships among attributes are not discussed here.

One classic multivariate InfoVis technique is parallel coordinates. This technique contains multiple vertically drawn, parallel lines, each representing a different attribute. The values of the attributes lie along these lines. Another set of lines, each representing an alternative, runs across parallel lines crossing parallel lines at the values of the variables for each record. Figure 3 is an illustration of parallel coordinates using XmdvTool (http://davis.wpi.edu/~xmdv), which is a public-domain tool. As the figure shows, although the technique of parallel coordinates is useful for detecting outliers and trends in a data set, following individual cases can be quite difficult, particularly with large data sets (e.g., numerous alternatives or options). An interactive tool that assists with the task of following individual alternatives or color-coding particular cases can facilitate the tracking of specific alternatives (Inselberg and Dimsdale 1990; Artero, Oliveira et al. 2004; Peng, Ward et al. 2004). However, multiple lines tend to overlap, which might alter the perception of the decision maker, causing confusion. Another variation of parallel coordinates is Parallel Bargram (Wittenburg, Lanning et al. 2001), implemented under the name of EZChooser (http://brisa.merl.com:8080/myezchooser/) or InfoZoom (http://www.infozoom.com/). In both implementations, each row represents an attribute, and no lines were drawn between data points. Thus, Parallel Bargram does not cause confusion due to overlap, but users need to use brushing or filtering techniques to identify individual data points. Figure 4 shows a screenshot of InfoZoom 5.0.

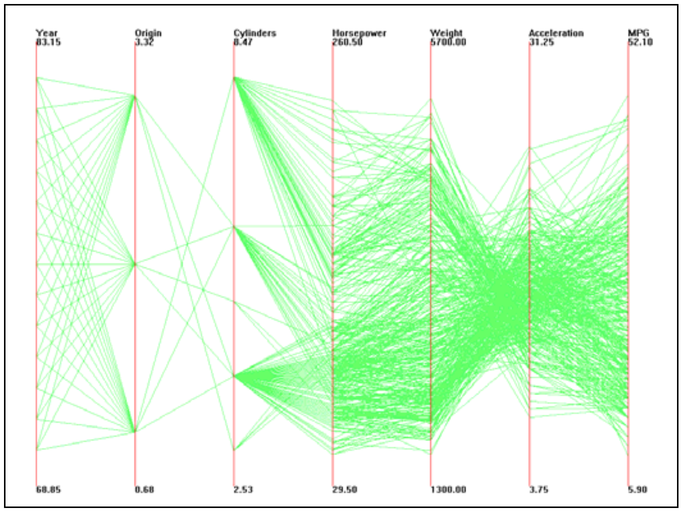

Figure 3. A screenshot of parallel coordinates

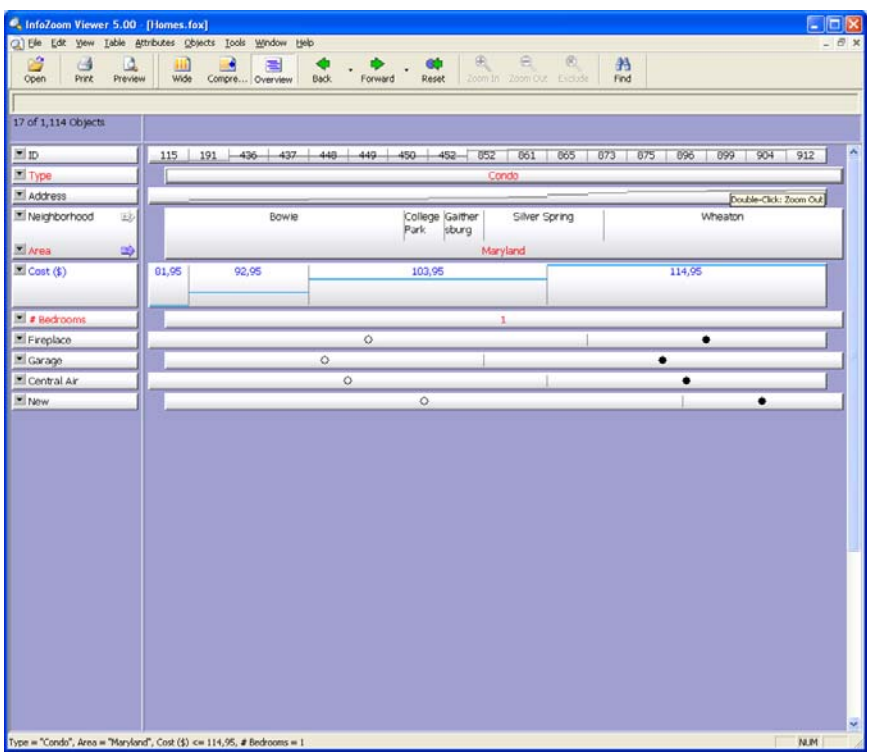

Figure 4. A screenshot of InfoZoom

Table Lens is another multivariate visualization tool based on a table view (Pirolli and Rao 1996). Figure 5 shows a commercialized implementation of the Table Lens technique, called “Eureka.” When zoomed in on, the presentation is very similar to a tabular view, except that it has horizontal bar graphs rather than simple character-based text and numbers representing the value of the cells (see Figure 6). When zoomed out from, it shows only fine bar graphs, as shown in Figure 5, which would be helpful to identify the trends and correlations between attributes. Because of the limited number of pixels, the detailed presentation of it is often sacrificed.

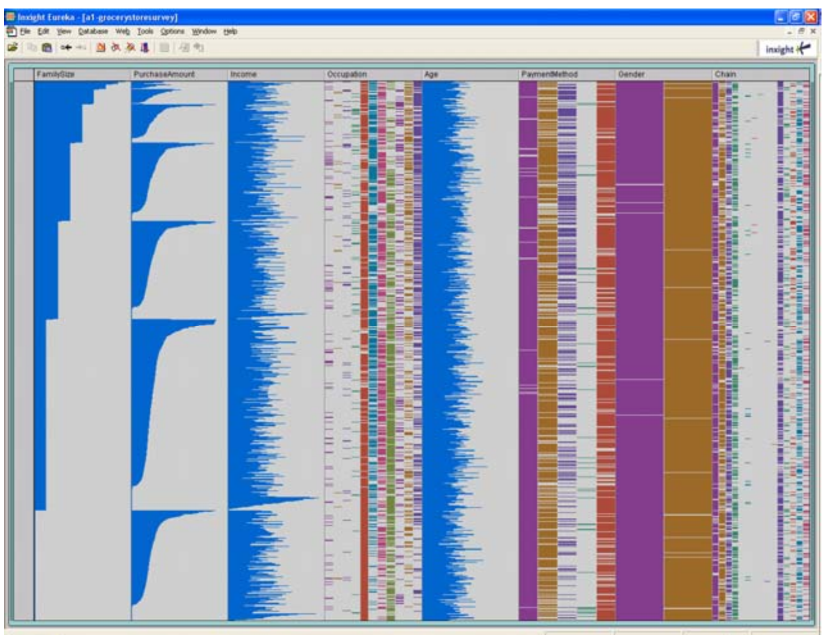

Figure 5. A screenshot of Table Lens

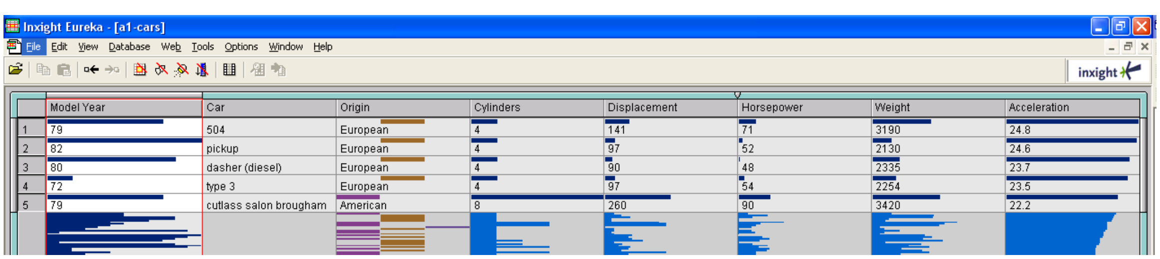

Figure 6. A screenshot of Table Lens with zoom-in

ValueCharts (Carenini and Loyd 2004) and ValueCharts+ (Bautista and Carenini 2006) are additional multivariate visualization techniques which are slightly similar with Table Lens. The data presentation of ValueCharts is based on a table-like paradigm and uses horizontal bars to represent values. However, the most interesting feature is that adjusting weights for attributes is possible by resizing the width of the column head. The total score for each alternative, automatically calculated and presented as another horizontal bar, allows the direct-manipulation of the attribute weights by a user, providing another natural way to support the WADD decision strategy without much cognitive burden placed on the user. In addition to this feature, many other features are added to support various cognitive tasks identified in the PVIT model (shown in Table 5).

Somewhat different from these multivariate InfoVis techniques is the Dust & Magnet technique (Yi, Melton et al. 2005), which uses a magnet metaphor to present multivariate information. As shown in Figure 7, each attribute is represented by a black square and works as a magnet. Each alternative is represented as a black dot and works as a dust particle. Depending on several factors (i.e., the value of a dust particle (or an alternative) and the size of the magnet (or the weight on an attribute)), the level of attraction between the dust particle and the magnet is determined, and the dust particle is attracted to the magnet. This model of attraction is a more natural and intuitive representation of the weighted additive model, or WADD strategy. Because it involves animated interaction, the Dust & Magnet technique is engaging and easy to understand.

In contrast, the location of each dust particle could be somewhat random, so retrieving a value for each dust particle requires additional interaction (i.e., clicking on the dust particle).

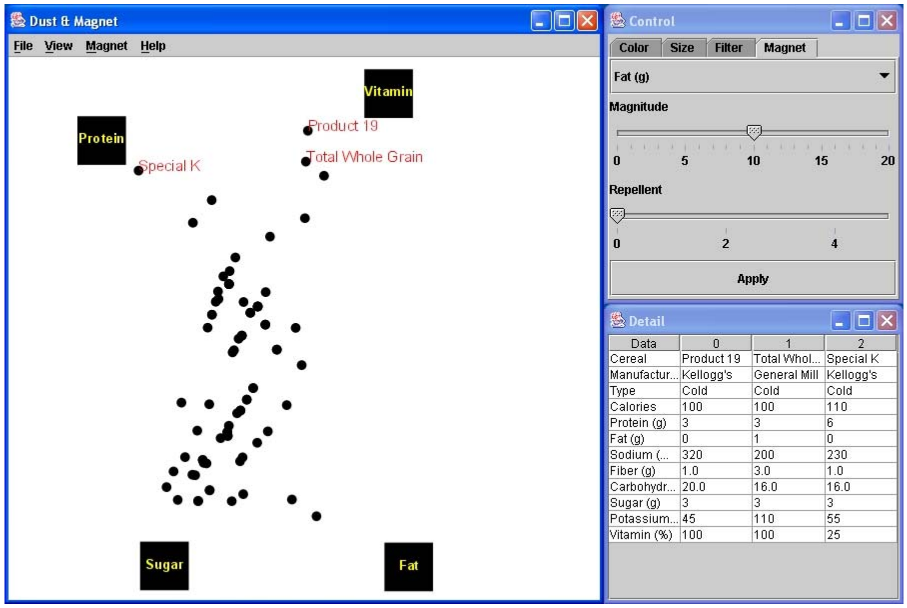

Figure 7. A screenshot of the Dust & Magnet technique

2.3.2.2 Interaction Techniques

Dynamic query is an interactive filtering mechanism. Traditional query interfaces (e.g., SQL language) require the formulation of complicated conditional statements that involve the use of specific non-natural language syntax to obtain a filtered data set; and an incorrect query statement necessitates more adjustment of the complicated conditional statement. Essentially, with traditional query interfaces, a trial and error approach is used. However, using dynamic query, a user can more visually interact with the system. By adjusting the dynamic query (e.g., changing the range of acceptable values or excluding specific values of attributes), the results are instantly changed, so the user can make sense of data set and quickly adjust the filtered data set (Shneiderman 1994).

Dynamic query has been utilized in many places. For example, Speier and Morris conducted an empirical study comparing a visual interface with a text-based interface (Speier and Morris 2003). The visual interface was actually Homefinder (Ahlberg and

Shneiderman 1994), which heavily uses a dynamic query interface. However, the text-based interface was a system showing the results in a tabular view. Interestingly, the results show that a visual interface is not always better than a text-based interface. Even though dynamic query is superior in filtering out unnecessary information, participants want to see detailed data in the end when they make a final decision. Thus, the text-based interface proved superior in the phase of final decision making. A more advanced form of dynamic query is the attribute explorer (Spence and Tweedie 1998), which shows distribution information while supporting the functionality of dynamic query. Thus, using attribute explorer, a decision maker can see the overall distribution before filtering out a subset of data.

Marking is another interaction technique used for keeping track of a certain data point (e.g., a decision alternative or particular attribute). Often, a user wants to trace where a data point (or alternative) is located within the overall dataset. For example, as shown in Figure 7, three data points are marked with red labels. The three data points are conspicuous even when mixed with other data points. The user can change various settings to redistribute the data points while still keeping track of how the relative position of the marked points changes when the parameters of the search, filter, or comparison change. This technique could be quite useful to keep the potentially best or most interesting alternative salient to the user while exploring the overall set of alternatives.

Since the amount of information often surpasses the resolution of a computer screen, any limitation in screen size should be mitigated. One classic method is zooming and panning. However, a zoomed-in view often loses the overview outside of its view. To overcome this problem, many other variations have been proposed. Such techniques are generally categorized into "Overview and Detail" and "Focus + Context." Overview and Detail techniques generally have multiple views that provide the overview and the detailed information separately. For example, Plaisant et al. (1995) provided a taxonomy of multiple views in the context of an image browser. In contrast, "Focus + Context" techniques often use a single view that provides an enhanced view of the area of interest and a less enhanced view of the surrounding areas. These techniques often entail distortion between the focused area and surrounding areas. Examples include the fisheye view (Sarkar and Brown 1994), the perspective wall (Mackinlay, Robertson et al. 1991), and DateLens (Bederson, Clamage et al. 2004). Yet another rather unconventional approach to overcome the limitation of screen real estate is to have a larger screen(s). The benefits and usability concerns have been researched by Czerwinski and her colleagues (Czerwinski, Smith et al. 2003; Robertson, Czerwinski et al. 2005).

2.3.2.3 Uncertainty Visualization

Pang defined uncertainty in InfoVis to "include statistical variations or spread, errors and differences, minimum-maximum range values, noisy, or missing data" (Pang, Wittenbrink et al. 1997, p.2). Several visualization methods have been proposed to present missing data, including the use of color, shading, reflectivity, bumpiness, animation, glyphs, and degraded graphical images (Pang, Wittenbrink et al. 1997; Finger and Bisantz 2002; Eaton, Plaisant et al. 2005).

In the context of a nursing home choice, missing data are a major cause of uncertainty. Thus, handling of data requires extra care, particularly when WADD strategies are used. Even though missing data are certainly different from value zero, they are often treated as zero values, so an alternative with missing data is unfairly penalized, producing a lower score than is possibly deserved. Instead, the use of average values could be a way to mitigate such a problem, but it may not be accurate, as the missing value may actually be substantially higher or lower than the average value of the distribution for the given attribute.

2.4 Decision Making + InfoVis

Direct linkage(s) between aforementioned decision strategies and InfoVis techniques is rather difficult since it is not clear which InfoVis techniques can support which decision strategies. For example, although identifying which InfoVis techniques support SAT and EBA decision strategies is difficult, one low-level cognitive tasks used in SAT and EBA is to “Filter out uninteresting alternatives (list creation).” Filtering is one of the basic InfoVis techniques as well, and dynamic query and attribute explorer can support filtering. As this example shows, low-level cognitive tasks can be used to connect terminologies from two separate domains. Collecting cognitive tasks and connecting decision strategies and InfoVis techniques have been done as follows:

First, low-level cognitive tasks required for decision making are listed. Even though cognitive tasks identified in the PVIT model are quite comprehensive (Bautista and Carenini 2006), most of them are solely designed to support compensatory or normative decision making strategies such as WADD, EQW, and MAU. Since decision makers use many other strategies as discussed before, some cognitive tasks used for decision strategies (i.e., MCD, VOT, SAT, EBA, MINIMAX, MAXIMAX, and LEX) are added to the PVIT model. In addition, low cognitive tasks of Amar et al. (2005) are also added since they use multivariate InfoVis techniques. Four cognitive tasks overlap with those in the PVIT model; three tasks (find extremum, characterize distribution, determine range) are newly added; and three (find anomalies, cluster, and correlate) are not considered here since they are less relevant in decision making. Second, decision strategies are added in the column of “Decision Strategies.” When a low level cognitive task supports multiple decision strategies, all decision strategies are listed together. Since EQW and WADD are simplified decision strategies of MAU, they tend to be listed together for a low level cognitive task. Third, examples of InfoVis techniques are added in the column of “InfoVis Techniques.” Because listing all the possible InfoVis techniques is not feasible, only the most salient examples are listed. Note that most of the compensatory strategies are implemented in ValueCharts since the ValueCharts are based on the PVIT model, but some newly-added tasks are not supported by ValueCharts, so other proper InfoVis examples are listed. Finally, the “ID” column is added to help refer to each cognitive task.

The resulting list of cognitive tasks with decision strategies and InfoVis techniques is shown in Table 12. The purpose of the VDM framework is to provide comprehensive cognitive tasks and the required InfoVis to help InfoVis designers and developers identify the link between decision strategies and InfoVis techniques so that they will select the proper InfoVis techniques that support particular decision strategies.

Note that cognitive tasks in the VDM framework fall into one of three categories: supporting compensatory decision strategies, supporting non-compensatory strategies, and supporting both. Cognitive tasks supporting both (i.e., cognitive tasks with ID 23-26 in Table 12) tend to be cognitive tasks that are not limited to decision making tasks. Matching InfoVis techniques can also be categorized in the same manner: InfoVis techniques supporting compensatory decision strategies and those supporting non-compensatory decision strategies, referred as “CV” and “NCV,” respectively, for convenience.

Since the nature of decision making is complex and often illogical, it is difficult to claim that the proposed VDM framework is complete. However, as illustrated in detail, some meaningful taxonomies of cognitive tasks are aggregated, so it is believed that they are quite comprehensive. The effectiveness of the VDM framework will be tested by applying it to nursing home choice.

Table 12. The Visualized Decision Making Framework (adapted from Amar, Eagan et al. 2005; Bautista and Carenini 2006)

Strategies [a]	Decision strategies [b]	ID	Low level cognitive tasks	Exemplar InfoVis techniques
C	EQW, WADD, MAU	1	Selection of objectives (hierarchy creation)	ValueCharts
	MAU	2	Definition of value function of each primitive objective	ValueCharts
	WADD, MAU	3	Determine initial objective weighting	ValueCharts, AHP
	EQW, WADD, MAU	4	Addition/modification of objectives at any point	ValueCharts, Dust & Magnet
	WADD, MAU	5	Inspection of hierarchy of objectives	ValueCharts
	MAU	6	Inspection of component value function	ValueCharts
	EQW, WADD, MAU	7	Inspection of range on which each primitive objective is defined	ValueCharts, parallel coordinates
	WADD, MAU	8	For each alternative, assessment of the contribution to total value of each objective	ValueCharts
	WADD, MAU	9	Assessment of the extent to which each objective weight contributes to total score	ValueCharts
	EQW, WADD, MAU	10	Comparison of alternatives with respect to total value	ValueCharts, Dust & Magnet
	WADD, MAU	11	Comparison of results among different evaluations	ValueCharts
	WADD, MAU	12	Sensitivity analysis of changing a weight	ValueCharts
	MAU	13	Sensitivity analysis of changing a component value function	ValueCharts
	MCD	14	Comparison of two alternatives and determine the winner [d]	-
	VOTE	15	Addition of marks for positive and negative attributes of each alternative [d]	-
NC	SAT, EBA	16	Addition/modification of each alternative at any point	Dynamic Query
	SAT, EBA	17	Filter out uninteresting alternatives (list creation)	Dynamic Query, Attribute Explorer
	MINIMAX, MAXIMAX, LEX	18	Find Extremum [c]	Color coding, Sorting
	SAT, EBA,	19	Characterize Distribution [c]	Attribute Explorer
	EBA	20	Determine Range [c]	Summary statistics
	LEX	21	Comparison of alternatives with respect to objective value	ValueCharts, Table Lens, Dust & Magnet
	SAT, EBA	22	Assessment of benchmark values, such as average and standard deviation [d]	-

Table 12 (continued).

NC, C	(All)	23	Inspection of domain values of each alternative	Table, Annotation
	(All)	24	Selection/marking of an alternative	Marking
	(All)	25	Maintain an overview of all relevant information	Table Lens, Overview + Detail, Focus + Context, Zooming
	(All)	26	Represent/display missing data	Uncertainty visualization

[a] Non-compensatory (NC) and compensatory (C) decision strategies
[b] Multi-Attribute Utility (MAU), Weighted Adding (WADD), Lexicographic (LEX), Lexicographic semi-order (LEXSEMI), Satisficing (SAT), Elimination-by-Aspects (EBA), Equal Weight (EQW), Majority of Confirming Dimensions (MCD), Feature Voting (VOTE), Maximize Minimum (MINIMAX), and Maximize Maximum (MAXIMAX)
[c] These tasks come from Amar et al.
[d] These tasks come from decision strategies

CHAPTER 3: REQUIREMENTS ANALYSIS

3.1 Purposes

The purpose of requirements analysis is to better understand the target users, who are individuals that are faced with choosing a nursing home for their loved ones. The more detailed aims include: 1) To identify the cognitive/decision processes used by decision makers when choosing a nursing home; 2) to identify the challenges experienced by decision makers while processing information on nursing homes; 3) to identify the information sources that individuals have previously relied on during decision making (e.g., the NHC website); and 4) to collect user opinions and feedback on these information sources.

3.2 Methods

3.2.1 Participants

The participants of this study include family members and/or friends of nursing home residents who have experience with choosing a nursing home for a loved one or anticipate having to make this choice in the near future. Ideal participants possessed fluency in English and the ability to describe the experience of choosing a nursing home, the ability to utilize a personal computer and the Internet to perform research, online shopping, or similar tasks, as well as normal or corrected-to-normal vision (e.g., sufficient vision for computer usage).

Recruitment of these specific participants was more challenging than expected. Initially, 64 nursing homes, located within a 20-mile radius of the metro Atlanta area, were contacted. The author and another assistant visited nursing homes or emailed and called the representatives of these nursing homes. However, facility representatives were generally not supportive of our research project due to potential security concerns, so this approach was insufficient to recruit enough participants. Another approach was to contact and visit local churches around metro Atlanta, which have elderly adult groups (e.g., a bible study group for the elderly). It was anticipated that these elderly adults would likely have the required qualifications or experiences for the purposes of this study. Unfortunately, however, most of the churches also turned out not to be optimal channels for participant recruitment. Representatives at churches mentioned that though they understood the good intent of the research, they could not actively support the project because the purpose of their church was not in line with the purpose of this research.

The most successful approach turned out to be recruiting participants through sending a mass email message to staff and faculty members at the Georgia Institute of Technology. The list that contains the names, email, and positions of about 5,000 staff and faculty members of Georgia Tech was obtained. After learning that the response rate to mass email is about 1% through a pilot test with 100 randomly-selected recipients, the invitation to this interview study was sent to additional 1,900 randomly-selected staff and faculty members at Georgia Tech hoping to recruit 20 participants. Eventually, 19 participants were recruited for this interview study. Table 13 summarizes the demographic information of these 19 participants. Interestingly, the demographic information is similar to the demographic patterns found in previous survey studies in nursing home decision making (Castle 2003).

Table 13. Summary of demographic information of participants

Characteristics	Summary statistics
Gender	Male: 2 Female: 17
Age (years)	Average 54.3 (Min: 32, Max: 63)
Education level	No official education: 0 Elementary school or equivalent: 0 Middle school or equivalent: 0 High school or equivalent: 7 College/University or equivalent: 6 Masters degree or equivalent: 4 Ph.D. degree or equivalent/higher: 2
Annual House Hold income	over $75,000: 13 $50,000-$74,000: 2 $25,000-$49,000: 3 under $25,000: 0
Comfort level in using a computer	Very comfortable: 7 Comfortable: 4 Neutral: 7 Uncomfortable: 0 Very uncomfortable: 0
Years of computer experiences	Mean: 16.3 (Min: 5, Max: 30)
Years of experiences in using the Internet and online services	Mean: 10.8 (Min: 3, Max: 25)
The average number of hours spent online weekly	Mean: 27.2 (Min: 2, Max: 50)
Previous experiences in choosing a nursing home	Yes: 14 No: 5 (These participant anticipated choosing a nursing home in the near future.)
The relationship with the person that you chose or will choose a nursing home for.	Daughter / Son: 9 Daughter in law / son in law: 2 Niece: 2 N/A: 5 Grand daughter: 1

3.2.2 Procedure

At the outset of the interview, participants were asked to sign an informed consent form and to fill out a survey that was designed to collect basic demographic information, the results of which is shown in Table 13. Before the actual interview began, the interviewer asked participants for permission to audio record their voices during the interview, after which the interview was recorded using a notebook computer with a software application called "Camtasia"[1]. To allow participants to access and (re)view any relevant information on the Internet, the interviews were conducted in a place where the Internet access is available (e.g., interviewee's offices or homes).

Interview questions were generally pertinent to the four previously-mentioned research purposes. However, the interview was conducted in a semi-structured manner since the study itself was still exploratory at this point. Whenever possible, participants were asked to demonstrate, using a notebook computer, how they collected and processed the information they used while choosing a nursing home. If participants agreed, their demonstration was also recorded using Camtasia.

Each interview session lasted for approximately an hour, following the order of the prepared questions, which are shown in Appendix C. However, when an interviewee emphasized or deviated to issues that were not covered by the prepared questions, the interviewer did not intervene. Instead, the interviewer tried to fully capture those issues as long as the interview could be finished within the allotted time. The recordings were transcribed and codified after interview.

[1] Camtasia is a audio/video recording software application of TechSmith (http://www.techsmith.com/camtasia.asp)

3.3 Results

The first question asked during the interview focused on what type of decision making procedure was used when choosing a nursing home. Most participants' answers did not deviate significantly from the following simplified procedure:

1) Collect information about nursing homes in the neighborhoods;
2) Narrow down to the best candidates;
3) Investigate these candidates; and
4) Make the final decision.

Only two participants responded that they did not perform the first step because they already knew a lot about nursing homes due to her profession (i.e., pre-arranged funeral sales) or prior experiences in helping others choose a nursing home facility. The remaining interviewees followed decision making procedures closely mirroring those listed above.

When asked about the largest difficulties experienced during the decision making process, eight out of 19 participants mentioned that the emotional hurdle to put their loved ones in a nursing home facility was the biggest challenge. One mentioned, "No body does it easily. It is the last corral. That's the last thing. It is almost warehouse. I have no choice. I feel helpless." This emotional hurdle seemed to be even more severe in cases where loved ones resisted moving into a nursing home. Three participants mentioned this issue, and one of them said, "Mom was usually agreeable, but she hates a nursing home. It's hard. It's not her home."

Besides this emotional hurdle, assessment of the qualities of nursing homes which are pertinent to steps 2 and 3 in the decision making procedure was certainly another difficulty. As shown in Table 14, five participants mentioned difficulties in assessing the qualities of nursing homes, three mentioned difficulties in finding good candidates, and two mentioned the overall bad quality of the nursing homes choices. As summarized in the table, various other issues were also identified.

Table 14. The biggest difficulties in choosing a nursing home

The biggest difficulties	Participants	Count
Emotional hurdle	P1, P7, P9, P10, P13, P17, P18, P19	8
Assessment of the qualities of nursing homes	P3, P4, P9, P11, P15	5
Resistance of care receiver	P10, P12, P14	3
A search for a good nursing home	P10, P11, P15	3
A lack of knowledge in the investigation procedure (e.g., "I didn't know where to start the research")	P2, P18	2
Long waiting list for available beds	P13, P14	2
Uncertainty (e.g., "I don't know what will happen to my loved one.")	P8, P9	2
Overall bad qualities of nursing home	P9, P16	2
Finance	P16	1
Legal matters	P18	1
Time pressures	P13	1

Another question asked during the interview focused on identifying the most important factors individuals felt should be used to judge and select a nursing home. While responses varied, there were some common themes. The most frequently mentioned factor (12 out of 19 interviewees) was the location or proximity to residents' friends or family members. Many interviewees wanted to visit their loved ones, so many of them wanted the location of the nursing home to be close to their home or work places. Other frequently mentioned factors were cost (8 out of 19), cleanliness (7 out of 19), quality (6 out of 19), and security/safety (5 out of 19). Note that a participant could respond multiple factors.

The next four questions dealt with how decision makers found nursing home information to evaluate the various factors. Table 16 summarizes the responses. When asked if they had enough information while choosing a nursing home, 12 out of 19 said "Yes," four said "No," and three responded neither "Yes" nor "No." These responses were unexpected not only because various important factors were identified in the previous question but also because the information regarding some factors, such as the attitude of staff, is difficult to obtain. However, many interviewees mentioned that they visited the nursing homes and comprehensively checked out the possible options. For example, one participant said, "Yes, I think so. We actually visited there, so I think that it is sufficient." One of the participants who responded "No" mentioned that they did not know what to ask when trying to select a nursing home. Another participant said, "You never have enough information," and emphasized that many unexpected things happened after she chose a nursing home for her loved one.

Table 15. Important factors in choosing a nursing home

Important factors	Participants	Count
Location / Proximity to friends or family	P1, P3, P4, P5, P8, P9, P10, P11, P13, P14, P17, P18	12
Cost	P2, P3, P4, P8, P9, P11, P12, P18	8
Cleanliness / odor	P8, P13, P15, P16, P17, P18, P19	7
Quality	P1, P2, P5, P9, P10, P11	6
Security / Safety	P4, P9, P10, P16, P19	5
Responsible care	P7, P11, P12, P16	4
Staff / resident ratio	P1, P3, P17	3
Staff's attitude / compassion	P13, P15, P19	3
Ranking / Inspection rates	P4, P14, P18	3
Dietary	P7, P8, P11	3
Entertaining activities	P8, P13, P16	3
Atmosphere	P2, P3	2
Open communication (staff issue?)	P7, P15	2
The length of waiting list	P2	1
The level of comfort	P6	1
Freedom to visit	P7	1
Availability of Medicaid	P12	1
The condition of other residents	P13	1
Freedom to have pets	P16	1
Freedom to have outside doctors	P17	1
Insurance coverage	P17	1
Availability of a private space	P17	1

Table 16. Responses to the questions regarding nursing home information search

Questions	Yes	No	Neither Yes nor No
Did you have enough information when you chose a nursing home? (Will you expect to have enough information when you choose a nursing home?)	12	4	3
Did you rely on the Internet to make your decision? (Will you rely on the Internet to amek your decision?)	5	14	
Have you ever visited the Nursing Home Compare Web site?	4	11	4
Do you think this Web site would be helpful to you in selecting a nursing home?	8	0	11

Even though many participants responded that they had enough information, only five individuals relied on the Internet to help make their decisions. These five participants found that the ratings, locations, and inspection reports of nursing homes were useful. One individual said, “If a nursing home doesn't have a website, we weren't interested in it anyway” because she felt that that a lack of website implies that the nursing home is not well maintained. However, participants who did not rely on the Internet expressed concerns over its use. For example, one participant mentioned, “Simply anything on the Internet is unreliable. You should go to the place. Even virtual tours are not that reliable. No substitute for actual talking to the people. It's about the loved one's welfare.” Another interviewee said, “I rely on what I saw. An individual website only says good things. I don't know how to interpret the information on government websites.”

Participants who used the Internet as information sources could not recall any specific websites. One participant said that 12 of her family members collectively gathered links to individual nursing homes’ websites to find more information about them. Two other participants used the state government’s website to find the list of nursing homes in their neighborhoods. Following this discussion, the interviewer showed interviewees the NHC website, which was discussed in the previous chapter. After allowing interviewees to navigate different parts of the website, they were asked if the website would be helpful in the selection of a nursing home. Eight interviewees expressed positive responses to this question. One interviewee said, “It's a good start. I have no complaint. I don't understand some of measures. I need more explanations.” Another said, “Yes, but you still need to visit them. Still, I want to talk to people in assisted living facility.”

In order to observe how participants utilize the information on the NHC website, the interviewer asked them to choose the best nursing home in their neighborhoods. However, many participants were not familiar with the website itself, so they could not effectively accomplish the task. Instead, they familiarized themselves by reviewing the quality scores of the nursing homes that they already knew. Unfortunately, as a result, the interviewer did not have a chance to fully understand what kinds of decision strategies were used when selecting a nursing home or comparing nursing homes.

However, some comments captured during interviews did shed some light on several important aspects of the decision. One important point is that the decision criteria vary depending on an individual's circumstance. One said, "The process is different for everybody… Different people have different criteria." Thus, the proposed InfoVis tool should be flexible enough to embrace different decision criteria. Another point is that many participants doubted that the quality information on some websites, such as the NHC site, reflects the true quality of the nursing homes. Several participants mentioned that having the quality information is good, but they cannot rely on the information. The value of visiting real nursing homes and talking to the administrators and current residents and their families were emphasized by many participants. Yet another aspect that the interviewer noticed during the interview was that the decision was often made under enormous time pressure and emotional strain. Sometimes, sudden accidents (e.g., hip fracture and stroke) experienced by loved ones caused this pressure by forcing the need to place the loved one in an assisted care facility almost immediately. In other cases, the emotional hardship experienced by decision makers caused them to postpone the decision until the absolute last moment possible.

3.4 Discussion

The results of interviews revealed that choosing a nursing home is a very challenging and complicated decision process. Even before collecting information about nursing homes, the very fact of having to place a loved one into a nursing home can cause emotional difficulties for the decision maker. While collecting relevant information, decision makers have to consider too many variables (e.g., location, cost, security, and the quality of care), and some information is even difficult to obtain as an individual decision maker since such information is not easily revealed by individual effort, such as visiting nursing homes. Decision makers often do not have enough background knowledge to investigate the various important aspects of nursing homes thoroughly. It is certainly a difficult decision.

From the perspective of information processing, although participants listed various factors as important, collecting and processing relevant information often appears to be done through individual effort. Individual decision makers often collect information through word of mouth from doctors, friends, and social workers. Interviewees emphasized the importance of visiting actual nursing homes and talking to the current residents in nursing homes and their family members. Many felt that they had sufficient information when they chose a nursing home. Interestingly, many interviewees did not rely on the Internet to collect information. Some participants even doubted the veracity of the information on the Internet since they believed that it may not truly reflect the quality of nursing homes.

However, appropriate quality information of nursing homes could help decision makers enormously. Even though making a crucial decision without visiting actual facilities would be still dangerous, visiting several nursing homes is difficult and time consuming, if not impossible under urgent circumstances. In this case, the quality information could help decision makers filter out unqualified nursing homes to save time and effort. Quality information might also alleviate some of the emotional burden by increasing the confidence of a decision maker. In addition, quality information may also reveal long-term trends of a nursing home.

Some interviewed participants showed positive responses when they were introduced to the NHC website. They appreciated the comprehensive quality information of nursing homes is at least publicly available. However, their positive perception did not necessarily mean that they could effectively utilize the provided information to make a choice. Most interviewees had a difficult time to familiarize themselves with the overall website and navigate through the content, so the interviewer failed to observe the decision making processes and identify the difficulties that decision makers may experience.

However, participants made some comment, which provided us with some insights: 1) Individual circumstances largely vary; 2) decision makers have general skepticism about the information on the Internet; and 3) a nursing home is often chosen under enormous time pressure and emotional strain. These aspects should be considered while designing a tool for the decision maker.

CHAPTER 4: VDM DEVELOPMENT

Chapter 4 discusses how an InfoVis tool, called "Visualized Decision Making (VDM)," was designed, implemented, and refined through evaluation. This chapter consists of the following three sections: design, evaluation, and implementation.

4.1 Design

The design of VDM should require creativity, but being creative does not indicate a lack of a systematic approach. Several resources helped the designer (the author) generate not only creative but also effective designs. One resource that the author relied on was the InfoVis taxonomy, archived from the literature review (refer to Tables 6, 7, 8, 9, 10, and 12 for details). Among the numerous InfoVis techniques listed in the taxonomies, the following techniques appear to be most relevant: multivariate InfoVis techniques and interaction techniques for filtering and sorting.

In addition, the taxonomy of low-level cognitive tasks for decision making was used to verify and conceptually test the InfoVis techniques employed in VDM. The taxonomy of cognitive tasks from the VDM framework is quite comprehensive, and some of the cognitive tasks may not be applicable to the decision making problem of selecting a nursing home. Thus, the only cognitive tasks pertinent to nursing home choice were selectively used to design the main representation technique.

Another resource that used by the author comes from Castle and Lowe (2005), who developed the following criteria to evaluate a Nursing Home Report Card: 1) It is well-structured; 2) it has aids for navigation; 3) it has explanations for factors/variables throughout the report card; 4) it addresses diversity among target audiences; 5) it helps consumers understand key fundamentals; 6) it assists consumers with determining preferences; 7) it minimizes cognitive complexity; 8) it helps to explain how and why to use quality information; and 9) it incorporates design in short, manageable segments.

4.1.1 Brainstorming

Based on these resources, the author had brainstorming sessions to gather and generate ideas for InfoVis techniques. Though numerous InfoVis techniques already exist, only a few InfoVis techniques have been exclusively designed and implemented for supporting decision making, such as nursing home choice. Thus, the author created several InfoVis techniques (e.g., Decision Boxes, Decision Overlay Slide, Decision Spectrum) supporting comparisons of multiple alternatives considering multiple attributes, and these InfoVis ideas were translated into paper-and-pencil prototypes.

After collecting various InfoVis ideas, the author attempted to select the main representation technique for VDM among these ideas. In order to select the most potential InfoVis technique, the author used the VDM framework shown in Table 12. First, as shown in Table 17, 11 out of 25 cognitive tasks pertinent to nursing home choice were selected. The remained 14 cognitive tasks were not used due to the following reasons: 1) some cognitive tasks are for multiple objectives; 2) some cognitive tasks are related with component value functions, which would unnecessarily complicate the design of an InfoVis tool; and 3) some cognitive tasks could be considered after finalizing the main representation technique. Details of selected and removed cognitive tasks were summarized with additional comments in Table 17.

Table 17. A subset of cognitive tasks used to evaluate InfoVis techniques

ID	Decision Strategies[a]	Cognitive Tasks[b]	Comments
1	C	~~Selection of objectives (hierarchy creation)~~	The decision has a single objective, so multiple objectives are not considered.
2	C	~~Definition of value function of each primitive objective~~	The decision has a single objective, so multiple objectives are not considered.
3	C	Determine initial objective weighting	
4	C	~~Addition/modification of objectives at any point~~	The decision has a single objective, so multiple objectives are not considered.
5	C	~~Inspection of hierarchy of objectives~~	The decision has a single objective, so multiple objectives are not considered.
6	C	~~Inspection of component value function~~	Component value functions are not considered because it many unnecessarily complicate the system.
7	C	~~Inspection of range on which each primitive objective is defined~~	The decision has a single objective, so multiple objectives are not considered.
8	C	~~For each alternative, assessment of the contribution to total value of each objective~~	The decision has a single objective, so multiple objectives are not considered.
9	C	Assessment of the extent to which each objective weight contributes to total	
10	C	Comparison of alternatives with respect to total value	
11	C	~~Comparison of results among different evaluations~~	Multiple evaluations are not considered because it many unnecessarily complicate the system.
12	C	Sensitivity analysis of changing a weight	
13	C	~~Sensitivity analysis of changing a component value function~~	Component value functions are not considered because it many unnecessarily complicate the system.
14	C	Comparison of two alternatives and determine the winner	
15	C	Addition of marks for positive and negative attributes of each alternative	
16	NC	~~Addition/modification of each alternative at any point~~	Alternatives and their values are not editable.
17	NC	Filter out uninteresting alternatives (list creation)	
18	NC	Find extremum	
19	NC	Characterize distribution	
20	NC	Determine range	
21	NC	~~Comparison of alternatives with respect to objective value~~	The decision has a single objective, so multiple objectives are not considered.
22	NC	~~Assessment of benchmark values, such as average and standard deviation~~	This cognitive task can be considered after the InfoVis tool is finalized.
23	Both	Inspection of domain values of each alternative	
24	Both	~~Selection/marking of an alternative~~	This cognitive task can be considered after the InfoVis tool is finalized.

Table 17 (continued).

25	Both	Maintain an overview of all relevant information	
26	Both	~~Represent/display missing data~~	This cognitive task can be considered after the InfoVis tool is finalized.

[a] Non-compensatory (NC) and compensatory (C) decision strategies
[b] Removed cognitive tasks for the evaluation of InfoVis techniques for this study were crossed out, and the background of the entire row is grayed out.

Table 18 shows a list of InfoVis techniques and cognitive tasks supported by different InfoVis techniques. Unfortunately, the author failed to find any prior studies which show the right way to identify whether a certain InfoVis technique supports a cognitive task, so the author constructed Table 18 with discretion. Of course, a single InfoVis technique can be implemented in different ways, and the variations may result in a quite different mapping table. However, the purpose of the evaluation was simply choosing the most appropriate representation technique for VDM, so the author believed that this ad hoc evaluation would be sufficient.

Table 18. A list of InfoVis techniques and supported cognitive tasks

InfoVis techniques	**Supported cognitive tasks**		
	Compensatory	Non-compensatory	Both
Multidimensional Scaling	3		25
ValueCharts	3, 9, 10, 12	18, 19, 20	23
Parallel Coordinates	15	17, 18, 19, 20	25
Dust & Magnet	3, 12	17, 18, 19, 20	25
Table Lens		17, 18, 19, 20	23, 25
Scatter Plot Matrix		18, 19, 20	25
Trellis Plot		18, 19, 20	25
Start Coordinates		18, 19, 20	25
Chernoff's Face		18	25
EZ-Chooser system		17, 18, 19, 20	23, 25
Decision Box*	3, 9, 10, 12, 14		23
Decision Overlay Slide*	3, 14, 15		
Decision Spectrum*		17, 19, 20	25
Stacked Histogram	9, 10		23

* InfoVis techniques were introduced during the brainstorming sessions.

According to this simple evaluation, the author found that ValueCharts supports many cognitive tasks, especially both compensatory and non-compensatory cognitive tasks. In addition, since it is based on familiar tabular view, a decision maker without prior knowledge about InfoVis can quickly understand how it works. Thus, the author decided to develop prototypes based on ValueCharts.

4.1.2 Prototypes

From literature review and requirements analysis, the author found that the computer literacy of target population may not be high enough to deal with complicated visualization system and also found that the location and proximity of nursing homes is most frequently considered as important factors by interviewees. Thus, while constructing prototypes, instead of exclusively using visualization techniques in ValueCharts, the author decided to use a map view to provide geographic information, resulting in "Decision Map," and break the ValueCharts into two pieces, "Decision Table" and "Decision Box," to lower the cognitive load. These three prototypes will be explained below.

Figure 8 shows a prototype that has an interactive map to show the locations of nursing homes in the neighborhoods. This prototype was inspired by HomeFinder (Williamson and Shneiderman 1992) and interactive web-based map services (e.g., Google Map[2], Yahoo Map[3], and Live Search Maps[4]). Since the location or proximity of a nursing home is an important factor to consider, the following prototype was designed to provide the distance between each nursing home and the anchor location, such as a decision maker's home or office. Sometimes, multiple anchor points should be

[2] http://maps.google.com
[3] http://maps.yahoo.com
[4] http://maps.live.com

considered: For example, when a decision maker has multiple siblings, they want to find a nursing home which is closely located to all of the siblings. Thus, the prototype has an ability to add multiple anchor points, and the "total distance" column on the right side shows the summation of the distances between a nursing home and multiple anchor points.

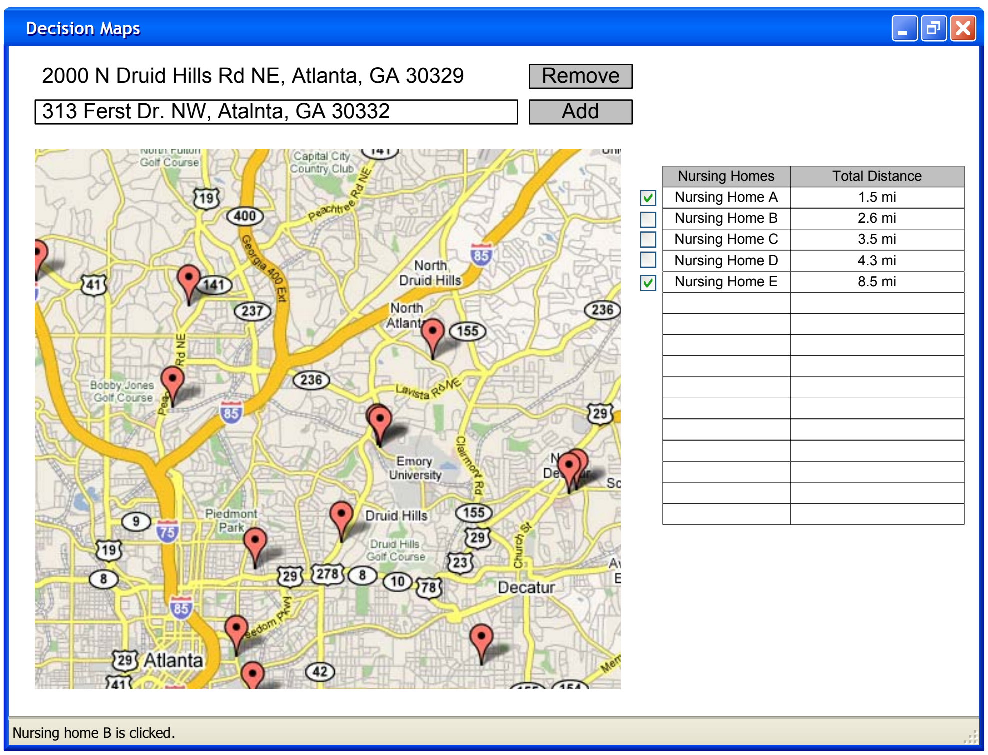

Figure 8. Decision Map

Figure 9 shows Decision Table. The main purpose of this prototype is to visualize quality information of nursing homes comprehensively, so that a decision maker can see the overview and quickly eliminate the poorly rated nursing homes. Since traditional column headers cannot afford lengthy titles of nursing quality measures, the fisheye view and a step-like layout were used to present all of the measures. If one of the columns, or attributes, is highlighted, the corresponding column title is enlarged. In addition, a quality measure that is worse than state-wide average or nation-wide average is encoded in red, so that a decision maker can quickly notice poorly rated nursing homes in the dataset.

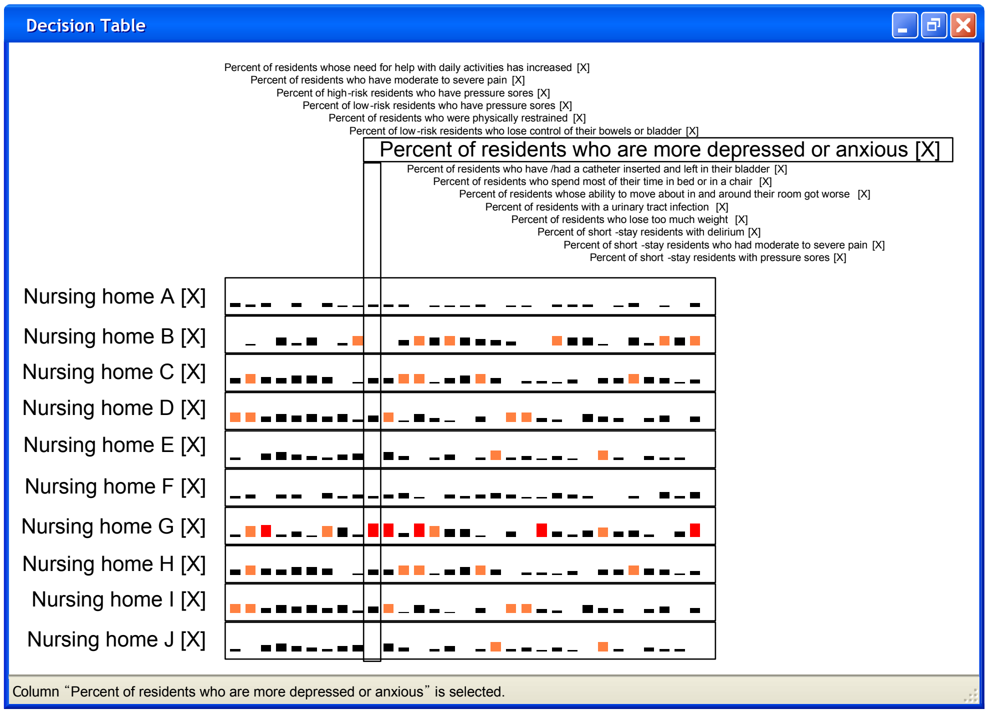

Figure 9. Decision Table

Figure 10 shows another prototype that allows a side-by-side comparison between two nursing homes. In this view, a decision maker cannot comprehensively review information. However, the decision maker can adjust weights of different attributes by changing the height of each box, which represents an attribute. In Figure 10, the "Pressure Sore" box, which is surrounded by a red dashed rectangle, has a bigger weight than the other attributes in the decision since the Pressure Sore box has a bigger height. The total risks of the two compared nursing homes are presented at the bottom of the screen. On the right side, the detailed description of the currently selected (or surrounded by a red dashed rectangle) attribute is also shown.

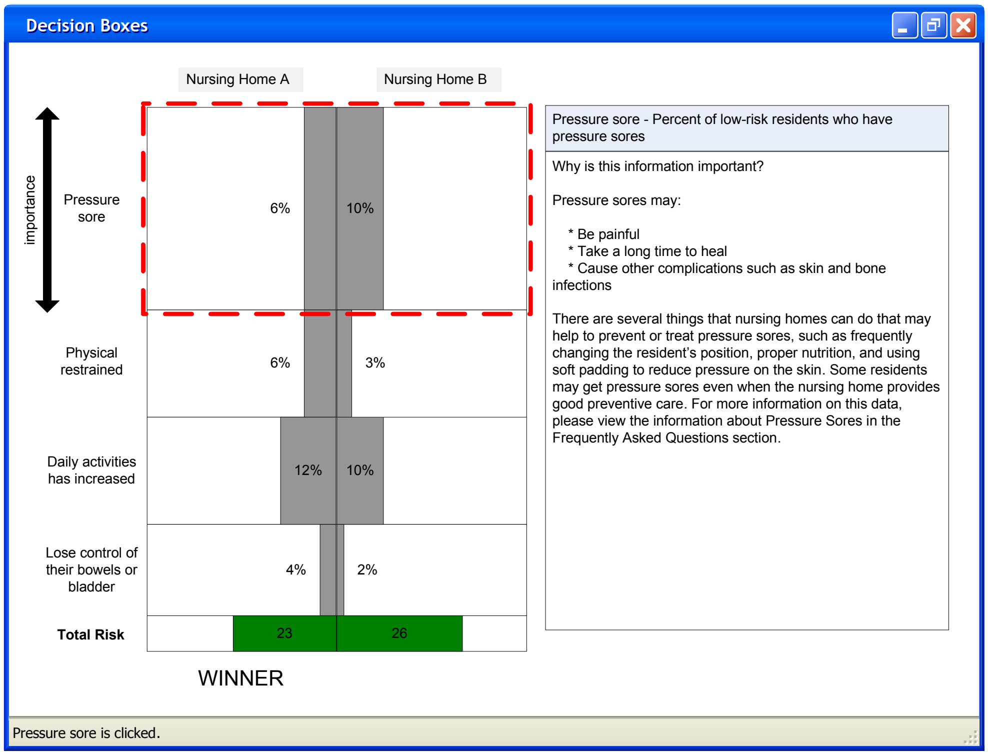

Figure 10. Decision Box

These three prototypes could be used separately, but they might work together since they have their own advantages and disadvantages.

4.1.3 Working Prototypes

Even though the prototypes clearly visualize how different aspects of visual elements work, the interactive elements of these tool made it difficult to verbally describe to potential users how they work. Thus, the author developed interactive working prototypes using some of web technologies (e.g., JavaScript, CSS, Ruby on Rails, and MySQL). The following pictures are screen shots of these working prototypes.

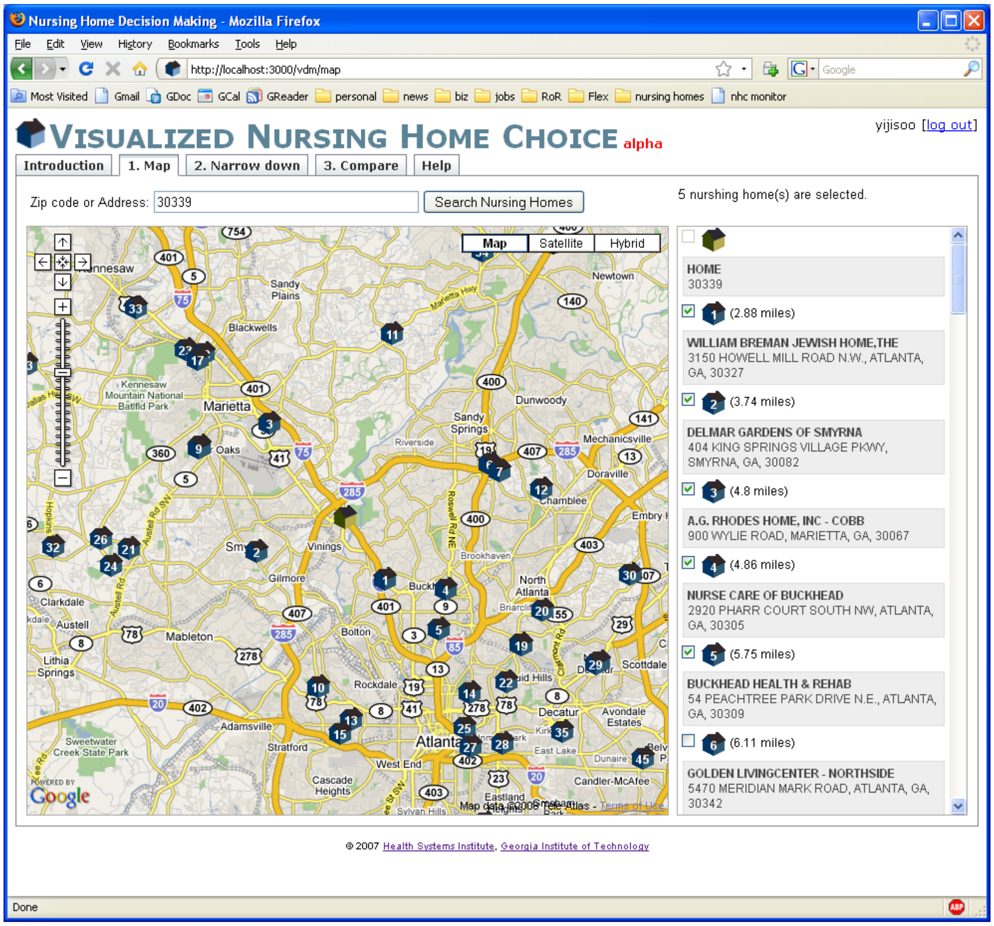

Figure 11. Decision Map - working prototype

While the Decision Table was implemented, the author realized that the step-like presentation of attributes consumes lots of space, so no space remains to present the detailed description of each attribute. Thus, the top yellow area was used to present the detailed information of each attribute, and the contents of the top yellow area were designed to change as a user hovers a mouse cursor on top of any of the column headers.

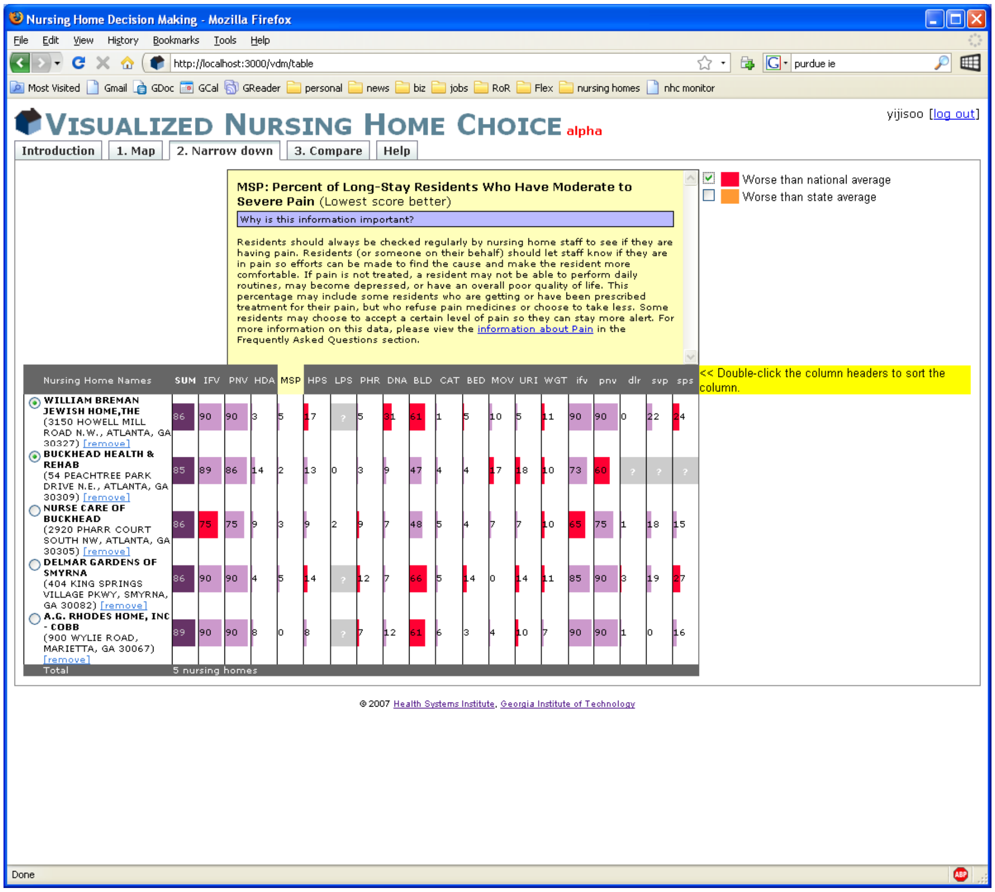

Figure 12. Decision Table - working prototype

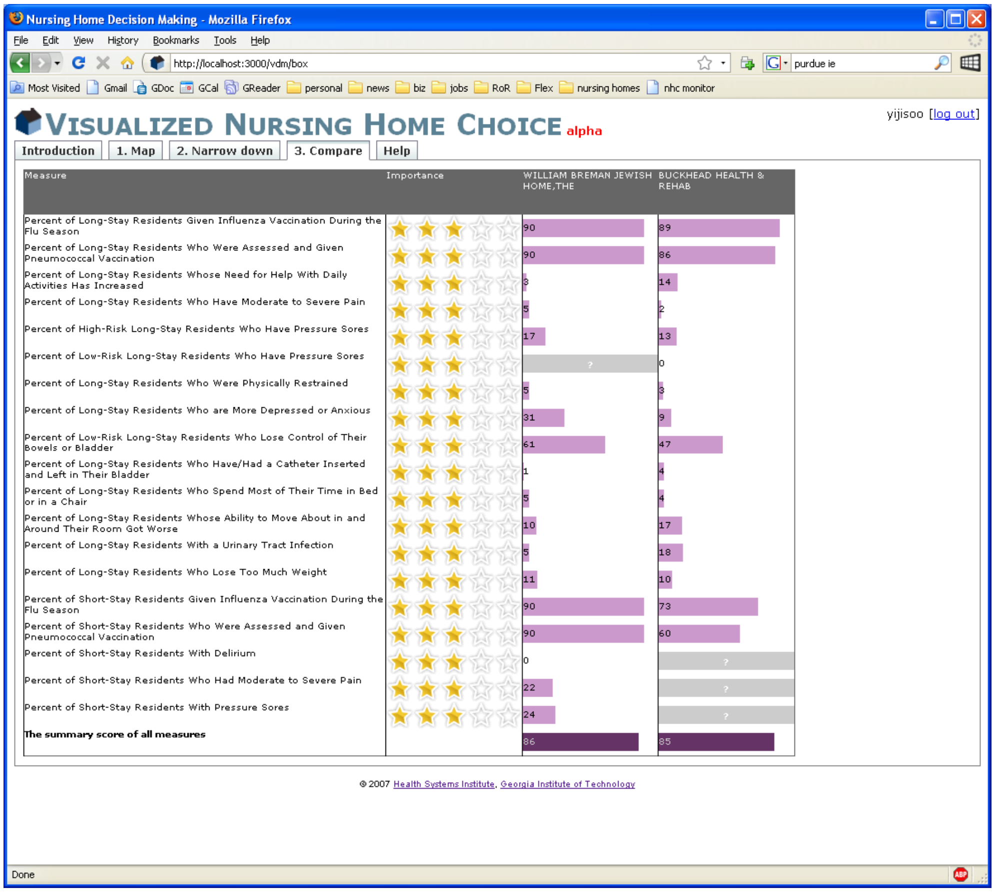

Figure 13. Decision Boxes - working prototype

4.2 Evaluation

Initially, multiple evaluation studies were planned after generating different levels of prototypes, such as paper-and-pencil prototypes, prototypes, and working prototypes. However, the author found that communicating the features of the proposed InfoVis techniques without working prototypes was challenging. Thus, after preparing preliminary working prototypes, the participants of the interview study in requirements analysis were asked to review the working prototypes and provide some feedback. This was a simplified evaluation study to understand whether the visualization concepts were well understood or not. First, the participants were shown the NHC website and the implemented working prototypes. They were asked what are the pros and cons of the two different websites. Their feedback was transcribed and codified in Table 19.

Table 19. The comparison between the NHC website and the working prototype

	Pros	**Cons**
The NHC website	The filtering with a distance (1)* The state/nation-wide averages (2) Simple bar graphs (5) Easy navigation (1) More comprehensive information (1)	Difficult navigation (e.g., more steps to reach a certain page (5), and wrong locations of the “next” button (2)) Poor instruction (2) A lack of the map of nursing homes (1) Separation between explanation and graphs (1) Too much explanation (1)
The working prototype	Less steps (4) Ability to see all of the measure in a screen (6) The map of nursing homes (3) More interaction (1) The definition on top (2)	Difficult navigation (1) Illegible numbers (1) Confusing color encoding (3) A lack of instruction and legends (3) Cryptic abbreviations on column headers Too much information in one screen (2) A lack of some measures (1) A lack of filtering with a distance (2) A lack of the state/nation-wide averages (1) Inconsistent directions of bar charts (1) Difficult to use Decision Box (2)
Common Issues		Difficult measures (1)

* Note: The numbers in parentheses are the numbers of participants who mentioned the particular issues.

Even though the author collected some negative feedback, the overall feedback received was positive. As shown in Table 19, having the entire information in a single page was favored by some of interviewees. For example, after seeing the NHC website, one said, “I need to print out all of the information, and compare them side-by-side, but I am glad to have this.” Then, after seeing the working prototype, “It lines up all for me! It saves my time.” Through this collective view, many navigation problems in the NHC website seemed to be resolved.

However, as just mentioned, the early prototype of this system had lots of feedback regarding minor issues, such as lack of instruction, illegible numbers, and confusing color encoding. However, one of critical issues was about Decision Box. Even though Decision Box provides a side-by-side comparison between two nursing homes, some interviewees complained that the weighting of different attributes set on Decision Box was not shown in the Decision Table, so it was confusing. This problem was also resolved.

4.3 Implementation

As anticipated, the implementation of VDM was challenging since conventional user interface components embedded in the user interface framework did not support the proposed visualization techniques. However, several other visualization toolkits such as Piccolo (Bederson, Meyer et al. 2000) and Prefuse/Flare (Heer, Card et al. 2005) support more advanced InfoVis techniques. They are also publicly available and may be helpful to implement the proposed design.

One important requirement for implementation is that VDM should be accessible via the World Wide Web and used through popular Web browsers such as Microsoft Internet Explorer and Mozilla Firefox. The advantages of this requirement are as follows: 1) The prototypes or unfinished versions could easily be accessed by recruited users, so rapid and instant feedback can be collected; 2) multiple participants can access this system, so it is possible to conduct multiple experiments simultaneously using web technologies; and 3) after the study ends, disseminating the final version of VDM will be easy and convenient.

Due to this requirement, initially, JavaScript and AJAX technologies were considered to implement VDM. However, even though many interactive web services, such as Gmail, have been implemented using these technologies, these technologies have the following disadvantages to implement an InfoVis tool on the web environment: 1) The visual representations are limited by HTML; 2) different browsers responded differently to some of JavaScript and CSS; and 3) implementing interactive interface or animation require enormous effort. Thus, the original working prototype implemented using JavaScript and AJAX technologies did not evolve quickly to provide required features.

Fortunately, while searching for alternative technologies, Abode Inc. released Flex Builder 3 and Jeff Heer released the alpha version of Flare, which is a simplified ActionScript version of Prefuse. Using these technologies, the author could avoid many problems introduced by JavaScript and AJAX technologies. Thus, the whole system was re-implemented using Flex. At the same time, the server-side script language was switched from php to Ruby on Rails (RoR). Since RoR provides strict a Model-View-Control framework, after setting up a working system, adding new features and changing data structure cost less effort. MySQL was used as underlying database, and Ruby scripts were developed to import the nursing home data from the NHC website to the database, so that VDM has the real nursing home data. Google Map API was used to implement Decision Map.

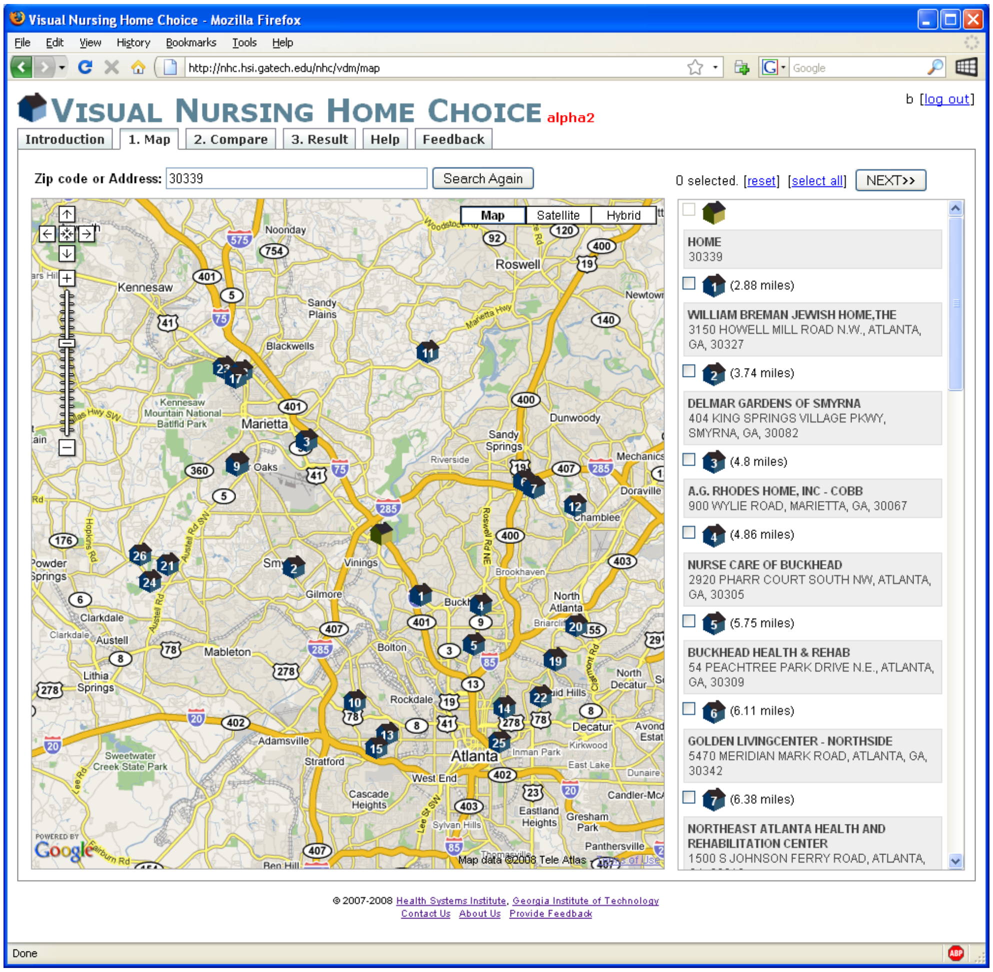

Figure 14. Decision Map - the final prototype

Even though the Decision Map was not changed during implementation, several features were added while switching to a new set of technologies. One change was that Decision Table and Decision Box were merged to help users browse the overview and comparison at the same time as show in Figure 15. Thus, a slider bar to change the weight of selected attribute was placed on the top yellow box of the Decision Table. As the weight is changed, the column width of the corresponding column was also changed to reflect the change of the weight. A special column, called “SUM” column was moved to the left to show the weighted summary of all of the values more clearly. As participants requested, the color encoding was simplified as well. In the original prototype, positive measures (the highest score better) and negative measures (the lowest score better) were mixed in the same table, so additional color encoding was needed, which caused confusion. Thus, all of the measures were changed to negative measures to make the directions consistent, and the color encoding was removed. In the original design, a column separator was able to be dragged, so that one can directly manipulate column width without moving a mouse cursor to the slider bar. However, having two interaction methods for a single approach could be confusing to participants, so this interaction option was dropped from design consideration. However, if well designed, this design option could be useful since it provides more direct manipulation.

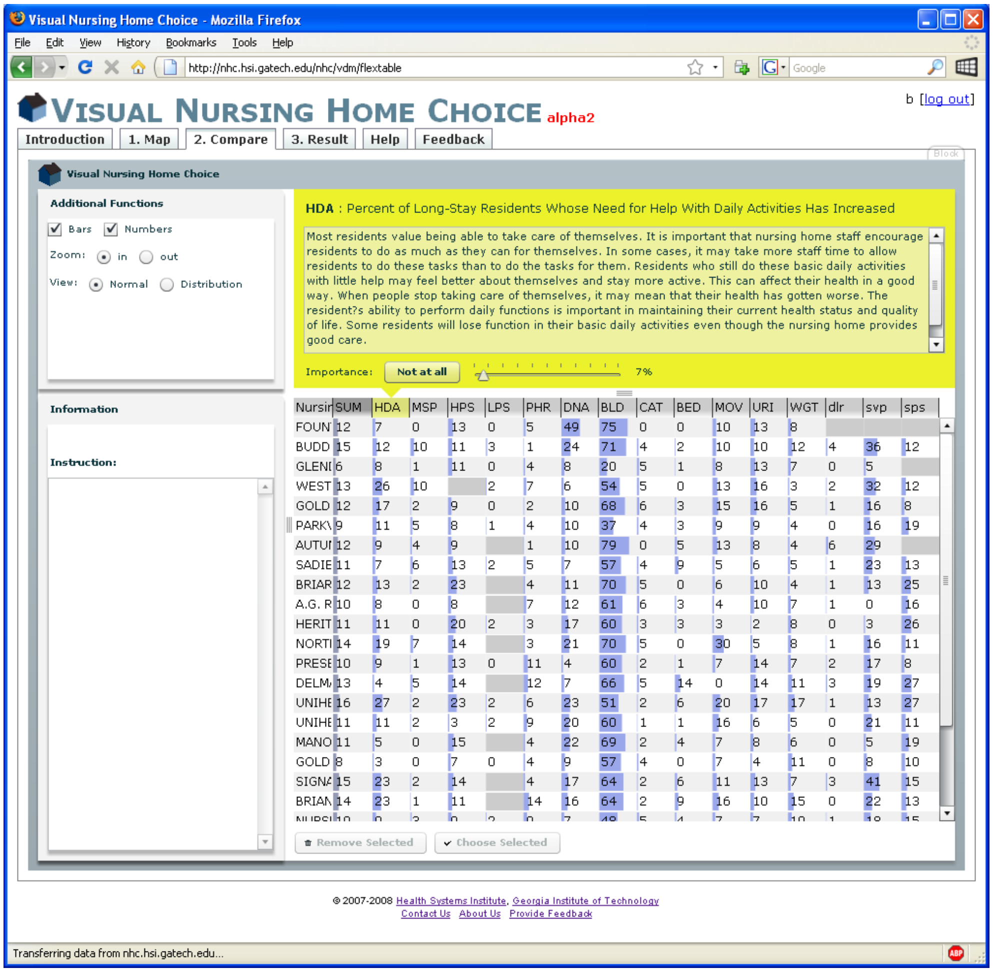

Figure 15. Decision Table - the final prototype

Another feature that was added to Decision Table was the distribution view. The distribution view is a feature to supplement the ValueCharts that do not support several non-compensatory strategies, such as filtering out uninteresting alternatives, finding extremum, and characterizing distribution. Figure 16 shows a screen shot of Decision Table with the distribution view. When the distribution view is used, every column is sorted at the same time, so that a decision maker can quickly understand the overall trend of the data. For example, in Figure 16, one can quickly notice that the values of the column of BLD (Percentage of Low-Risk Long-Stay Residents Who Lose Control of Their Bowels or Bladder) tend to have higher values than the values of other columns.

One also can notice what the minimum and maximum values of each column are. The effectiveness of the distribution view can be enhanced together with using the zoomed-out view as shown in Figure 17 since all the values can be shown without scrolling up and down. Because all of the columns are sorted at the same time, the values of a nursing home are not shown in one row any more. When a nursing home is highlighted, different rows on each column, which are corresponding to the highlighted nursing home, are highlighted. This can also help a decision maker find out where the different values of a nursing home fall within the distribution of values for a given attribute.

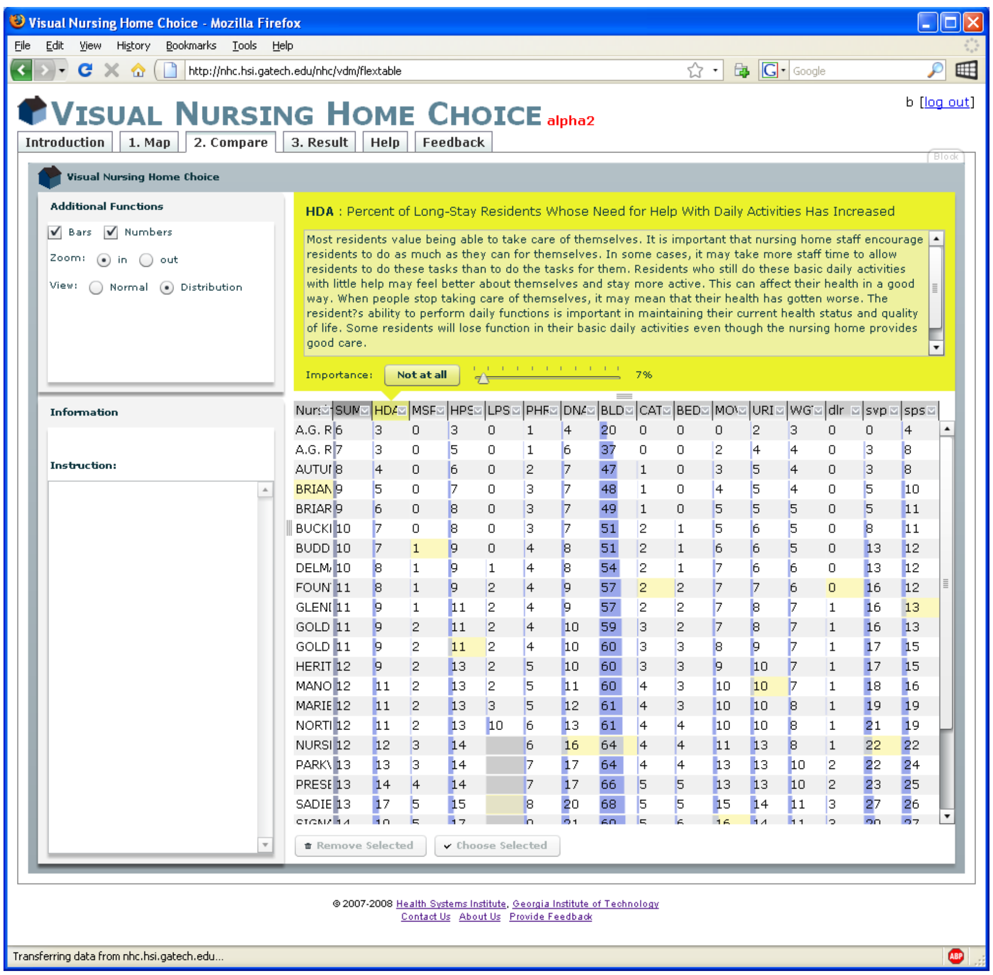

Figure 16. Decision Table using the distribution view

In addition, several auxiliary features were implemented. One is a comprehensive behavior-logging feature to record users' interactions, such as the uses of the weighting slider bar, the distribution view, zooming in/out, and sorting feature. Archived behavioral patterns have been important sources of information to understand users' behaviors and intents. The data communication between VDM and the underlying web server is done through XML, so changing the attributes and data is a matter of simply changing the XML contents. Smooth animation is another small benefit of using Flex.

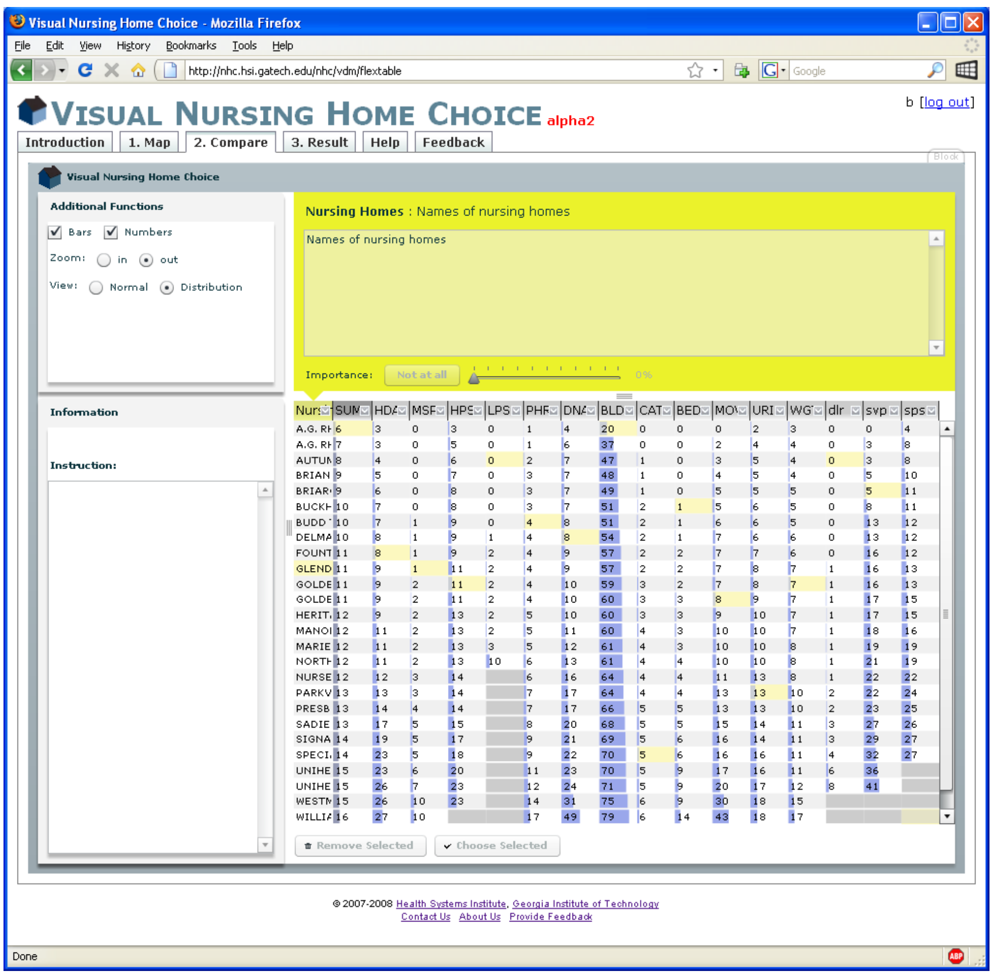

Figure 17. Decision Table using the distribution and zoomed-out views

After finishing the implementation, the members of Center for Interactive Systems Engineering in Health Systems Institute and students in the Human Centered Computing in the College of Computing at Georgia Tech reviewed and provided feedback on the usability of the implemented system. The identified glitches were fixed.

4.4 Discussion

Through an iterative procedure of designing, evaluating, and implementing, VDM was implemented. Several design ideas and prototypes have been generated, and they were evaluated using the VDM framework. An ad hoc evaluation showed that ValueCharts (Carenini and Loyd 2004) could support both compensatory and non-compensatory cognitive tasks in a balanced manner, so the final prototype of VDM was designed and implemented largely based on ValueCharts.

In order to get feedback from users, working prototypes were implemented in a relatively early stage in the development process. Because the InfoVis techniques were interactive and unfamiliar to many users, collecting feedback with static prototypes was difficult. Since users could play with working prototypes, they could provide more direct feedback on VDM. Certainly, having working prototypes would have some disadvantages (e.g., limiting the creativity of users), but it was an inevitable choice.

The final prototype of VDM consisted of two different parts: the Decision Map and the Decision Table. The Decision Map was added since one of the most important factors in nursing home choice is the location of nursing homes. Since the Decision Map provides an interactive map, a decision maker could choose a nursing home considering contextual information (e.g., the locations of homes, offices, and hospitals). The Decision Table is a variant implementation of ValueCharts. Several additional features were implemented to support various cognitive tasks: the weighting slider bar, the "SUM" column, and the distribution view. The weighting slider bar and the "SUM" column were designed to lower cognitive load of compensatory strategies. The distribution view was designed to promote more compensatory strategies while a decision maker uses non-compensatory strategies. These visualization techniques were ultimately expected to support more accurate and less cognitively-burdensome decisions.

While implementing the working and final prototypes, the author encountered various technical hurdles: First, finding appropriate technologies to implement InfoVis techniques was time-consuming and required trials-and-errors. Second, some user interface and visualization frameworks did not support the required visual representations and interaction techniques, so most of the visual components were built from scratch.

Fortunately, however, the final prototype system was successfully built, and VDM was ready to be open to the public. Besides the visualization techniques for decision making, the tool has small auxiliary features including zoom-in/out, turn on/off bars and numbers, sorting, and detailed description on the top. Then, the question becomes whether these techniques are actually helpful to the target population or not, which will be discussed in the Chapter 5.

CHAPTER 5: USAGE STUDY

5.1 Purposes

The purpose of the usage study was to demonstrate the effectiveness of the InfoVis techniques on the proposed InfoVis tool through an empirical study. As shown in the previous chapter, two different types of InfoVis techniques were proposed: the weighting slider bar and the "SUM" column, which are compensatory InfoVis techniques ("CV"), and the distribution view, which is non-compensatory InfoVis technique ("NCV"). To show the effects of these InfoVis techniques in the support of decision making and overcoming information overload, these two groups of InfoVis techniques have been compared through a web-based experiment. In addition, the amount of information was also varied to reveal any interactions between these InfoVis methods and the severity of information overload. The amount of information was varied in two ways: varying the number of attributes and varying the number of alternatives. Since a column and a row represented an attribute and an alternative, respectively, in VDM, the factor of the number of attributes was referred as "Width", and the factor of the number of alternatives was referred as "Height." The Width factor consisted of two levels (i.e., Wide and Narrow), and the Height factor consisted of in two levels (i.e., Long and Short). Thus, the Wide-Long condition was expected to introduce the highest severity of information overload among the four within-subject conditions, and the Narrow-Short condition lowest.

5.2 Hypotheses

The purpose of the usage study was translated into four main themes: 1) The effects of the different InfoVis techniques (i.e., CV and NCV) on decision quality; 2) the effects of the different amounts of information (i.e., Width and Height) on decision quality; 3) the interaction effects between the different InfoVis techniques (i.e., CV and NCV) and the different amounts of information (i.e., Width and Height) on decision quality; and 4) the effects of the different InfoVis techniques (i.e., CV and NCV) on perceived usability. Here, decision quality was measured with quantitative measures (i.e., decision accuracy, time to make decisions) and qualitative measures (i.e., the level of satisfaction, confidence, confusion, and time pressures); perceived usability was measured with the perceived ease of use, the perceived usefulness, the intensity of flow (involvement), the intensity of flow (control), and aesthetic quality. These four themes were elaborated into the four testable hypotheses (H1, H2, H3, and H4) below. In order to more succinctly present the hypotheses, a notation for a mathematical function was borrowed. Thus, "Decision Quality (x)" and "Perceived Usability (x)" mean the decision quality and perceived usability under condition x. For example, "Decision Quality (Narrow-Short, CV)" means the quality of decisions made with presence of the CV under the Narrow-Short condition.

- H1: The presence of CV, NCV, or both CV and NCV increases decision quality.
    - H1a: Decision Quality (CV) > Decision Quality (None)
    - H1b: Decision Quality (NCV) > Decision Quality (None)
    - H1c: Decision Quality (CV + NCV) > Decision Quality (None)
    - H1d: Decision Quality (CV + NCV) > Decision Quality (CV)

- H1e: Decision Quality (CV + NCV) > Decision Quality (NCV)

- H2: Decisions made with the large amount of information have lower decision quality.
  - H2a: Decision Quality (Wide-Short) < Decision Quality (Narrow-Short)
  - H2b: Decision Quality (Narrow-Long) < Decision Quality (Narrow-Short)
  - H2c: Decision Quality (Wide-Long) < Decision Quality (Narrow-Short)
  - H2d: Decision Quality (Wide-Long) < Decision Quality (Wide-Short)
  - H2e: Decision Quality (Wide-Long) < Decision Quality (Narrow-Long)
- H3: Decisions made with the larger amount of information are more affected under conditions in which either CV or NCV are absent.
  - H3a: Decision Quality (Narrow-Short) - Decision Quality (Wide-Short) > Decision Quality (Narrow-Short, CV/NCV/Both) - Decision Quality (Wide-Short, CV/NCV/Both)
  - H3b: Decision Quality (Narrow-Short) - Decision Quality (Narrow-Long) > Decision Quality (Narrow-Short, CV/NCV/Both) - Decision Quality (Narrow-Long, CV/NCV/Both)
  - H3c: Decision Quality (Narrow-Short) - Decision Quality (Wide-Long) > Decision Quality (Narrow-Short, CV/NCV/Both) - Decision Quality (Wide-Long, CV/NCV/Both)
  - H3d: Decision Quality (Wide-Short) - Decision Quality (Wide-Long) > Decision Quality (Wide-Short, CV/NCV/Both) - Decision Quality (Wide-Long, CV/NCV/Both)

- H3e: Decision Quality (Narrow-Long) - Decision Quality (Wide-Long) > Decision Quality (Narrow-Long, CV/NCV/Both) - Decision Quality (Wide-Long, CV/NCV/Both)

- H4: The presence of CV, NCV, or both CV and NCV increases perceived usability.
  - H4a: Perceived Usability (CV) > Perceived Usability (None)
  - H4b: Perceived Usability (NCV) > Perceived Usability (None)
  - H4c: Perceived Usability (CV + NCV) > Perceived Usability (None)
  - H4d: Perceived Usability (CV + NCV) > Perceived Usability (CV)
  - H4e: Perceived Usability (CV + NCV) > Perceived Usability (NCV)

5.3 Methods

In order to test the given hypotheses, a web-based experiment was designed and conducted. Generally, a web-based experiment has following benefits: 1) Ease of access to a large number of demographically and culturally diverse participants; 2) ease of access to rare and specific participant populations; 3) cost savings related to laboratory space, personnel hours, equipment, and administration; and 4) high external validity (Reips 2002). Since the experiment required a large number of participants from a specific participant population, a web-based experiment was a natural choice for this study.

However, a web-based experiment is often subject to the following problems: 1) Possible multiple submissions; 2) less control over the experimental design; 3) the self-selection problem; 4) dropout; 5) the misinterpretation of instructions; and 6) a lack of comparative basis for the web experiment methods (Reips 2002). These issues were carefully handled while designing the experiment website, and the details of how these issues were addressed will be discussed in the following sections.

5.3.1 Experimental Design

The experiment employed a mixed repeated-measures design with two between-subject factors (i.e., the presence/absence of CV and the presence/absence of NCV) and two within-subject factors (i.e, many alternatives ("Long") / a few alternatives ("Short") and many attributes ("Wide") / a few attributes ("Narrow")). Since the absence or presence of either CV or NCV was a between-subject factor, a participant experienced only one of the four different user interfaces, which was expected to be less confusing than experiencing four different user interfaces. Instead, participants performed a nursing home choice task four times under four different conditions (i.e., Wide-Long, Wide-Short, Narrow-Long, and Narrow-Short). Table 20 shows the sixteen different experimental conditions used in this study. For example, a participant performed a task only under the conditions of NCV-WL, NCV-WS, NCV-NL, and NCV-NS. Specifically, under the Wide condition, participant had fifteen attributes; in the Narrow condition, the participant had five attributes. In the Long condition, participants had seventy nursing homes; in the Short condition, participants had twenty nursing homes. When the CV was present, participants had the weighting slider bar and the "SUM" column; when the NCV was present, participants had the distribution view. When any of them is absent, the corresponding feature(s) were hidden in the interface.

Table 20. Design of Experiment of the Usage Study

		The amount of information			
InfoVis techniques		**Wide Long**	**Wide Short**	**Narrow Long**	**Narrow Short**
CV	**NCV**				
Absent	Absent	None-WL	None-WS	None-NL	None-NS
Absent	Present	NCV-WL	NCV-WS	NCV-NL	NCV-NS
Present	Absent	CV-WL	CV-WS	CV-NL	CV-NS
Present	Present	Both-WL	Both-Ws	Both-NL	Both-NS

5.3.2 Participants

As this experiment had four different conditions, varied by two between-subject factors, it required a substantial number of participants. Since approximately 20 participants were required for each between-subject condition, at least 80 participants were deemed to be necessary.

In order to recruit enough participants, various channels were explored. The email list of Georgia Tech staff and faculty members used for requirements analysis was utilized again. However, as experienced previously, the response rate from the Georgia Tech staff and faculty members was low, so we failed to recruit enough participants through this channel. Thus, the online caregiver communities listed in Table 21 were visited, and an invitation to the web-based study was posted on the various communities' bulletin boards or sent to the moderators of the communities via email. Some caregiver communities were very sensitive to this kind of invitation to research since they experienced several marketing scams previously. However, after explaining the intent of this study, the author received permissions from most of these caregiver communities, and, some negative communities members surprisingly became positive and enthusiastically supported this project.

Table 21. Caregiver communities

Community names	URLs	Invitation activities
Alzheimer's Association	http://www.alz.org	Posted an invitation
ElderCare Online™	http://www.ec-online.net	Posted two articles in the News & Research and Casual Corner sections
My Care Community	http://www.mycarecommunity.org	Posted an invitation
Revolution Health.com	http://www.revolutionhealth.com/ groups/caregivers/discussions	Posted an invitation
Children of Aging Parents	http://www.CAPS4caregivers.org (group: http://health.groups.yahoo.com/group/chck_thmpsn/links)	Registered in their mailing list, and send out an invitation
ElderCare Rights Alliance	http://www.eldercarerights.org	Left a message to the representative
Well Spouse Association	http://www.wellspouse.org	Email a couple of WSA Support Groups leaders
National Family Caregivers Association	http://www.thefamilycaregiver.org	Posted an invitation on their bulletin board

In order to attract more participants and motivate participants to complete the entire experiment and surveys, potential participants were promised to be compensated with a gift card worth 10 USD. Additional gift cards were also promised to those participants whose performance would rank within top ten percentages. The additional gift cards were expected to help motivate participants to perform their best while completing experimental tasks.

The qualifications of participants were identical with those of interviewees for requirements analysis. The ideal participants would have the following qualifications: 1) experience in researching and selecting a skilled nursing facility or nursing home in the past two years; or anticipate a need to research and select a nursing home within the next five years; 2) fluency in English and the ability to describe the experience of choosing a nursing home; 3) ability to utilize a personal computer and the Internet to perform research, online shopping, or similar tasks; and 4) normal or corrected-to-normal vision (i.e., sufficient vision for computer usage). These qualifications were explicitly mentioned in invitations, emails, and the introduction page of the experiment website in order to recruit the only qualified participants.

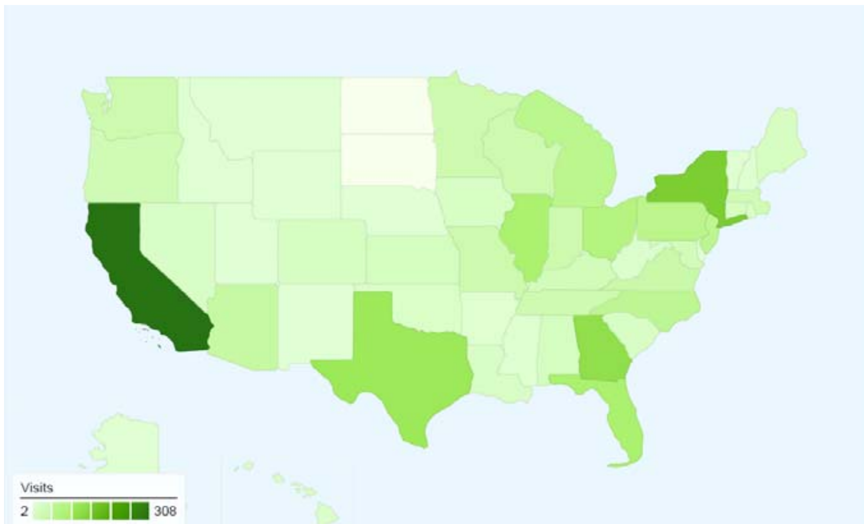

Figure 18. The geographical distribution of unique visitors

Table 22. The top ten states from which unique visitors came

States	The number of unique visitors
California	308
New York	155
Georgia	129
Texas	115
Illinois	94
Florida	94
Ohio	78
Pennsylvania	68
Michigan	65
New Jersey	61

Eventually, 2,036 unique visitors from various regions of the U.S. visited the experiment website. Figure 18 and Table 22 shows where the participants were geographically located. Among them, 314 visitors signed up for the experiment. Among those signed users, 92 dropped out, and the 222 completed the surveys and experiment — the completion rate was about 70%. However, the experimental results recorded in the database showed that many participants were not serious about their participation. For example, some participants spent only 2 seconds to select a nursing home out of 70 nursing homes on the list, which is hardly believed to be a behavior of a sincere participant. Thus, various criteria have been considered to find only sincere and valid participation, such as participants who spent more than 10 seconds for each task, participants whose decision accuracy is better than 0.2, and participants who do not make any meaningless comments (e.g., "blahblah") in the open ended questions in surveys. However, these criteria may introduce biases to the results because of the following reasons: 1) some criteria use one of the outcome measures (e.g., decision accuracy and time), and 2) some criteria are too subjective when the criteria are based on the comments in the survey.

Instead, the author found another indicator which helped the author screen out insincere participants without introducing bias. The indicator was the "tutorial completion ratio," which was driven from (time spent on the tutorial page) / (the length of a video tutorial). Each participant was supposed to watch the entire vedio tutorial before the actual experiment was started. If the time spent on the tutorial page is shorter than the length of the video tutorial (i.e., tutorial completion ratio < 1.0), then the participant did not watch the entire video tutorial.

Figure 19 show the relationship between the tutorial completion ratio and the average decision accuracy of four different trials[5]. As shown in the graph, there is a clear

[5] The method for deriving these accuracies will be discussed in the following sections. Accuracy is 1.0 if the best nursing home was chosen, and accuracy is 0.0 if the worst nursing home was chosen.

separation between participants who spent enough time on the tutorial page (tutorial completion ratio >= 1.0; sincere group) and participants who spent less time than the length of the video tutorial (tutorial completion ratio < 1.0; non-sincere group).

The average accuracies of the two groups are also distinctive. The average accuracies of the sincere group are highly condensed around 0.9, which is very accurate, while the average accuracies of the non-sincere group are randomly distributed. Of course, some participants have very high tutorial completion ratio (around 14.0), which might imply that the participant opened the tutorial page but paid his or her attention to other things. These participants also should be categorized as non-sincere participants since they probably did not pay proper attention to the video tutorial.

After investigating the detailed records of participants, the author decided that the participants whose tutorial completion ratio is between 1.0 and 4.0 are sincere. Figure 20 shows the histogram of count of participants in this range. Based on this screening method, the author assumed that the data from 115 participants are valid, with further analyses based on this subset of participants.

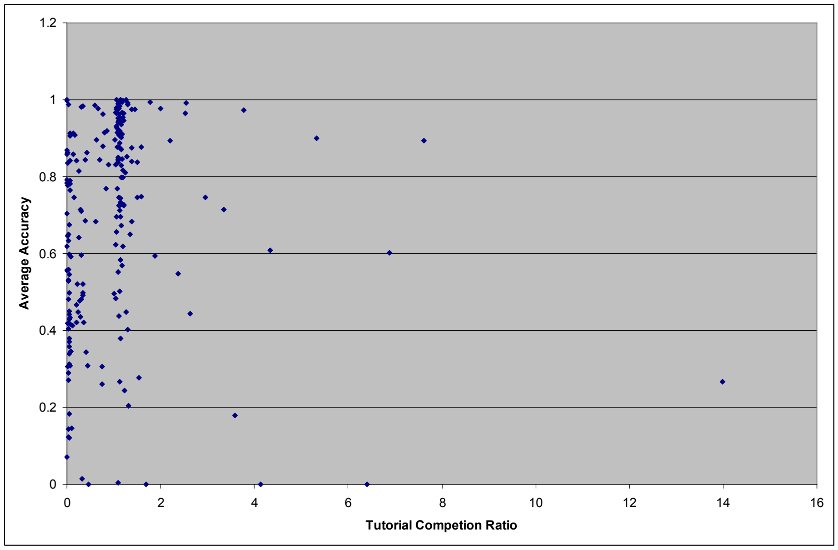

Figure 19. A scatter plot of tutorial completion ratio vs. average accuracy

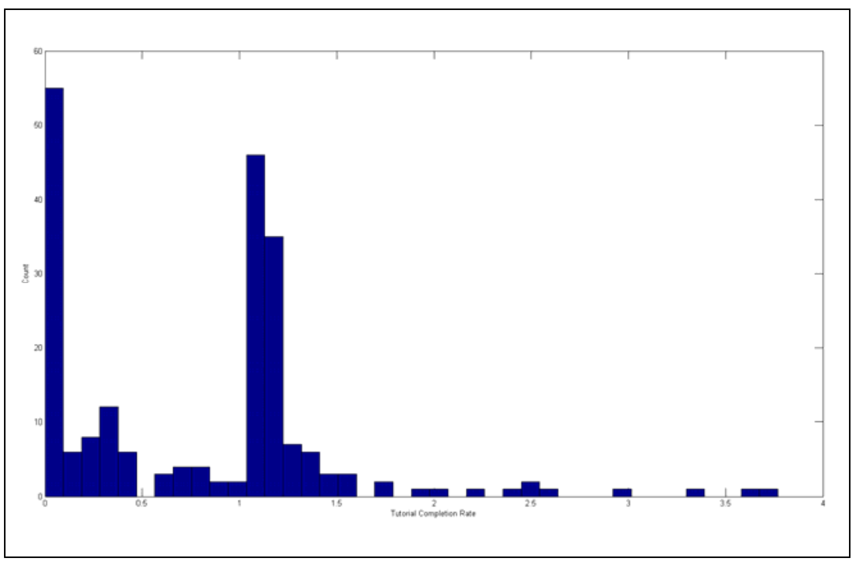

Figure 20. A histogram of tutorial completion ratio

The original 222 participants were randomly assigned to one of four conditions, so 56, 56, 55, and 55 participants were assigned to Both, CV, NCV, and None groups, respectively. As alluded by the number of participants for four groups, the balanced random assignment was conducted. However, after participation sincerity screening, 23, 30, 30, and 32 participants were remained for Both, CV, NCV, and None groups, respectively. Tables 23, 24, and 25 show the demographic information, computer literacy, and nursing home experience of these valid participants. As shown in the three tables, participants in the four different experimental groups do not show statistically significant differences at the error level of 0.05 in various measures. Statistical differences were tested using either the Chi-square test for ordinal or nominal measures (e.g., gender and education level) or the ANOVA test for scalar measures (e.g., age).

Table 23. Basic demographic information

	Both	CV	NCV	None	Total	Test
Age						
Mean (Stddev)	33.17 (9.124)	34.93 (11.531)	37.93 (10.010)	38.34 (10.667)	36.31 (10.519)	F = 1.51 p = 0.216
Gender						
Male	4	11	5	5	25	$\chi^2 = 5.3$ p= 0.148
Female	19	19	25	27	90	
Total	23	30	30	32	115	
Annual Income						
< $30,000	3	3	4	4	14	$\chi^2 = 11.5$ p = 0.484
$30,001 - $50,000	2	6	9	7	24	
$50,001 - $75,000	11	12	4	9	36	
$75,001 - $100,000	3	4	8	8	23	
> $100,001	4	5	5	4	18	
Total	23	30	30	32	115	
Education level						
Middle school	0	1	0	0	1	$\chi^2 = 6.1$ p = 0.907
High school	7	7	6	6	26	
College/University	13	16	16	20	65	
Masters degree	3	5	6	5	19	
Ph.D. degree	0	1	2	1	4	
Total	23	30	30	32	115	

Table 24. Computer literacy

	Both	CV	NCV	None	Total	Test
Computer Comfort Level						
Very uncomfortable	0	3	4	6	13	$\chi^2 = 10.6$ p = 0.563
Uncomfortable	0	0	1	0	1	
Neutral	0	1	1	1	3	
Comfortable	3	2	5	4	14	
Very comfortable	20	24	19	21	84	
Total	23	30	30	32	115	
Internet Experience						
Less than 1 year	1	0	0	0	1	$\chi^2 = 11.2$ p = 0.264
1 - 5 years	1	2	1	2	6	
5 - 10 years	11	13	6	10	40	
More than 10 years	10	15	23	20	68	
Total	23	30	30	32	115	

Table 25. Nursing home experience

	Both	CV	NCV	None	Total	Test
Have you ever selected a nursing home before?						
Yes	13	17	16	16	62	$\chi^2 = 0.356$
No	10	13	14	16	53	$p = 0.949$
Total	23	30	30	32	115	
Approximately how long ago did you finalize selection of the nursing home? (in years)						
Mean	1.42	1.43	0.76	1.8	1.35	F = 0.739
(Stddev)	(2.11)	(3.65)	(1.03)	(3.32)	(2.77)	p = 0.531
How many nursing homes did you visit before making your final decision?						
Mean	5.15	5.12	4.69	4.13	4.76	F= 0.510
(Stddev)	(2.609)	(3.199)	(1.662)	(2.825)	(2.616)	p = 0.677
How many times, on average, did you visit a nursing home before making your final decision?						
Mean	2.46	3.53	3.38	4.19	3.44	F = 0.646
(Stddev)	(1.05)	(3.184)	(3.222)	(4.578)	(3.307)	p = 0.588
How long did you research nursing home prior to making your decision? (in years)						
Mean	0.423	0.513	0.303	0.739	0.503	F = 0.664
(Stddev)	(1.038)	(1.126)	(0.49)	(1.862)	(1.25)	p = 0.576
Have you ever visited a nursing home before?						
Yes	2	1	2	1	6	$\chi^2 = 1.45$
No	8	12	12	15	47	$p = 0.693$
Total	10	13	14	16	53	

5.3.3 Equipment

The equipment for this web-based experiment consists of the server-side equipment and the client-side equipment. On the server side, the required equipment is simply a web server that provides surveys and experimental information to the participants. The experiment website uses the MySQL database management system and Ruby on Rails server-side script engine. The website not only delivered the proper contents (e.g., instructions, a video tutorial, and VDM) to participants but also collected information from participants during completion of the experimental tasks. For the surveys, a separate survey authoring and publishing tool, called SurveyMonkey, was used.

On the client side, each participant needed a personal computer with a web browser and an Internet connection to connect to the experiment website:

http://nhc.hsi.gatech.edu. Since an experimenter could not control the experimental environment directly, more attention was paid to the design of the experiment website to minimize any confusion. For example, the tabs on the top indicate in the current status; important instructions were written in a bold with a bright yellow background; and buttons labeled with “NEXT >>” were consistently used to guide participants to the next step. In spite of this guidance, a participant may press the back button of a web browser application. Pressing the back button allows the participant to divert from the predefined procedure, which might introduce unexpected noise into the experiment. However, unfortunately, preventing or disabling the back button using commonly available web technologies is difficult and not recommended due to security reasons. Thus, right after a participant signed up for the experiment, a warning message of “From now on, please do NOT press the ‘BACK’ button of your browser” was shown clearly. In addition, whenever a participant proceeded to the next page, the underlying system recorded timestamps, which were available for further investigation if necessary.

Web browser compatibility was another issue. Since we cannot control which web browser a participant used, the experiment website was thoroughly tested with the most popular browsers such as Microsoft Internet Explorer 6 and 7, Firefox 2.0, and Apple Safari 3.0. While conducting the experiment, few complaints regarding browser compatibility were reported. Two participants using AOL Browser complained that the experimental screens were not correctly displayed. However, after these individuals were advised to use an alternative web browser, such as Firefox 2.0, these two participants reported successful completion of the experiment. Even though the entire experiment website was thoroughly tested with different web browsers, some participants may have different configuration due to some reasons. For example, one might disable JavaScript or may not have the most recent Flash player installed. It should be noted that both JavaScript and Flash are intensely used in the experiment website to provide the interactive user interface. To prevent any unexpected behavior of the experiment website, we embedded JavaScript codes to make sure that JavaScript is enabled and the recent Flash player was installed. If they are not properly configured, warning messages were shown on the Introduction page.

Another important issue in this web experiment is the security issue. Since the pre-task and post-task surveys contain some questions that might reveal some private information, the data transmission while completing the surveys was secured by secure sockets layer (SSL), which encrypted the data transmission between client web browsers and the web server hosting the survey. Except for the two surveys, other steps of the experiment were provided by a different web server and database management system. The database was password protected, and no identity information was stored in the database.

In addition, Table 26 summarized the potential problems, which were discussed at the beginning of this chapter, and the plans used to counteract these problems.

Table 26. Potential problems of web-base experiments and the counter-plans

Potential problems	Counter-plans
Possible multiple submissions	Participants' IP addresses were collected, and no identical IP addresses were found among valid participations. (No multiple submissions were found among invalid participations.)
Less control over the experimental design	The website was carefully designed to minimize the confusion of participants, and the detailed history of navigation of each participant was recorded with timestamps.
The self-selection problem	The invitation of the web-based experiment was disseminated through multiple channels.
Dropout	Monetary compensations were given to promote the completion of surveys and experimental tasks.
The misinterpretation of instruction	Instructions were reviewed by many other colleagues, and some important instructions were highlighted with yellow background and bigger text. A video tutorial was also made to give the detailed instruction. If one skipped the video tutorial, the participant was excluded from the data set for further analysis.
A lack of comparative basis for the web experimental methods	No reliable counter measure was available.
Low external validity	This concern is not applicable for this study since it is an evaluation study of a web-based tool. A web-based experiment actually increases the external validity of this study.

5.3.4 Procedure

Each participant followed the procedure as summarized in Table 27. A screen shot corresponding to each step is attached in Appendix E as well.

Table 27. Experimental Procedure of the Usage Study

Seq.	Steps	Descriptions
0	Introduction	The Introduction screen contains the important information such as the purpose of the experiment, a brief description of the procedure, qualification, and compensations. It also guides a participant to sign up with an ID and password. (Refer to Figure 24)
1	Consent Form	The consent form screen shows the plain text version of the consent form, and the participant can pass this section only if he or she clicks on a check box saying "I read and agree to the above consent form." (Refer to Figure 25)
2	Pre-Task Survey	Demographics, experience regarding a nursing home choice, computer skills, the importance ratings of nursing home quality measures, and a problem of the pre-survey were captured. (Refer to Figure 26)
3	Tutorial	A video tutorial was shown to explain the detailed feature of the tool and experimental procedures. The video tutorial had subtitles for the participants who do not have audio devices or suffer from hearing impairment. (Refer to Figure 27)
4	Experiment	One of four between-subject conditions (i.e., Both, CV, NCV, and None) was randomly chosen for a participant, and the participant was asked to complete four randomly-ordered trials (i.e., Wide Long, Wide Short, Narrow Long, and Narrow Short). Before starting the experimental tasks, a participant was allowed to try out the features during a practice session. After each trial, seven questions were asked to measure the subjective decision quality. (Refer to Figures 28 and 29)
5	Post-Task Survey	Usability of the tools, the updated importance ratings of nursing home quality measures, and other qualitative questions regarding the overall impressions were asked. (Refer to Figure 30)
6	Finished	This page showed the experimenters' appreciation to participants and provided the contact information for further inquiries. (Refer to Figure 31)

The nursing home data was carefully prepared since the characteristics of data, such as correlation between different attributes and information structure, could significantly affect the results of the experiment. For example, if different attributes are negatively correlated, participants would experience more trade-off cases, implying that a nursing home with a low risk in an attribute has a higher risk in another attribute.

In order to ensure that four different trials have the similar correlations among data without loosing the characteristics of nursing home data (e.g., the percentage of residents who have a bladder problem is generally bigger than 20%), data for the four trials were randomly sampled from the real nursing home data, and their averages of inter-correlation were controlled. The average of inter-correlation is simply the average of correlation coefficients of all of the possible pairs of attributes. The average of inter-attribute correlation cannot be more negative than -1 / (t – 1), where t is the number of attributes, and its maximum is 1.0 (Gleser 1972).

Since the number of attribute and the number of alternatives affect the proper level of the average of inter-attribute correlation, the proper averages of inter-attribute correlation were calculated by averaging the average of inter-attribute correlations of 10,000 random samples. Table 28 shows the averages of the averages of inter-attribute correlation.

Table 28. The average of the average of inter-attribute correlation

Conditions	The averages of the averages of inter-attribute correlation
Long/Wide	0.0033
Short/Wide	0.0420
Long/Narrow	0.0004
Short/Narrow	0.0051
Pilot	0.0213

In order to generate data which have these proper averages of inter-attribute correlation, another set of data were randomly sampled. Basically, nursing home data were randomly sampled from the database from the NHC website until the average of inter-attribute correlation of the sample data is close enough to the values in Table 28. This method not only generates random data which have proper inter-attribute correlation but also keep many commonly found trends of nursing home quality information since the data were sampled from the real dataset. The data of nursing homes that have missing information were excluded during the sampling.

In order to determine the proper number of nursing homes in the experimental data, top 10 and 91st - 100th cities in terms of population were surveyed. The numbers of nursing homes within 10 miles from the center of these cities were summarized in Table 29. According to this data, one can expect to have about 70 nursing homes to investigate if they live in major cities; another can expect to have at least 20 nursing homes to investigate even if they live in a smaller city. Thus, the numbers of nursing homes in the Long and Short conditions were determined to 70 and 20, respectively.

Table 29. The top 10 and 91st– 100th cities in terms of population and the number of nursing homes

Top 10 cities	**Number of nursing homes**	**91st to 100th cities**	**Number of nursing homes**
1. New York	128	91. Babylon	15
2. Los Angeles	152	92. Orlando	32
3. Chicago	94	93. Akron	35
4. Houston	34	94. Chula Vista	30
5. Phoenix	26	95. Lubbock	15
6. Philadelphia	85	96. Rochester	32
7. San Antonio	48	97. Laredo	6
8. San Diego	36	98. Modesto	13
9. Dallas	31	99. Reno	6
10. San Jose	38	100. Durham	14
	Average: 67.2		Average: 19.8

5.3.5 Tasks

The experimental task is basically to choose the best nursing home among four different data sets (i.e., Wide-Long, Wide-Short, Narrow-Long, and Narrow-Short). In the “Long” condition, 70 nursing homes were given; in the “Short” condition, 20 nursing homes were given. In the “Wide” condition, the 15 attributes were given; in the “Narrow” condition, the 5 attributes were given. Table 30 shows the attributes and whether each attribute belongs to the Wide or Narrow conditions.

Table 30. Nursing home quality measures used for the web-based experiment

Abbreviations and attributes	**Wide**	**Narrow**
HDA - Percent of Long-Stay Residents Whose Need for Help With Daily Activities Has Increased	Y	Y
MSP - Percent of Long-Stay Residents Who Have Moderate to Severe Pain	Y	Y
HPS - Percent of High-Risk Long-Stay Residents Who Have Pressure Sores	Y	Y
LPS - Percent of Low-Risk Long-Stay Residents Who Have Pressure Sores	Y	Y
BED - Percent of Long-Stay Residents Who Spend Most of Their Time in Bed or in a Chair	Y	Y
PHR - Percent of Long-Stay Residents Who Were Physically Restrained	Y	
DNA - Percent of Long-Stay Residents Who are More Depressed or Anxious	Y	
BLD - Percent of Low-Risk Long-Stay Residents Who Lose Control of Their Bowels or Bladder	Y	
CAT - Percent of Long-Stay Residents Who Have/Had a Catheter Inserted and Left in Their Bladder	Y	
MOV - Percent of Long-Stay Residents Whose Ability to Move About in and Around Their Room Got Worse	Y	
URI - Percent of Long-Stay Residents With a Urinary Tract Infection	Y	
WGT - Percent of Long-Stay Residents Who Lose Too Much Weight	Y	
dlr - Percent of Short-Stay Residents With Delirium	Y	
svp - Percent of Short-Stay Residents Who Had Moderate to Severe Pain	Y	
sps - Percent of Short-Stay Residents With Pressure Sores	Y	

Since participants may have very different experiences while choosing a nursing home or since some participants may have not chosen a nursing home yet, different participants may choose different nursing homes based on different criteria. Thus, the following imaginary scenario was given to participants:

"On a Sunday afternoon, you got a phone call from Jane, one of your best friends. In a trembling voice, she said that her 75 year old father fell down this morning and broke his hip again. The hospital said that the injury is permanent due to multiple fractures and his thin bones, so he should move back home after the treatment. Even though he is mentally healthy, he cannot move at all and needs constant care. Unfortunately, she cannot take care of him due to her full time job, so she painfully decided to find a nursing home for him. Looking for a good nursing home is not easy, either. There are so many nursing homes in her neighborhood. To help her choose a good nursing home, a doctor gave her a list of common quality measures of nursing homes, but she was so overwhelmed and could not pay attention to the details of the list. So, she asked you to read the list.

Please read through the following quality measures and rate their importance based on the condition of Jane's father (hip fracture)."

However, the scenario did not provide detailed preference structure of Jane, so that each participant experience mental overload while figuring out the proper preference structure. The preference structures were captured before and after the experimental tasks.

5.3.6 Measures

Detailed demographic information, such as annual household income, age, and ethnic group, were measured since Agnelelli et al. (2006) found that these demographic factors showed significant influences on nursing home choices.

Time pressure is another important aspect in this particular decision making process. According to the survey study of Castle et al. (Castle 2003, p.51), most decision makers choose a nursing home within a few days. In order to simulate a similar decision making environment for the web study, we introduced a time limit to complete the task. After conducting a pilot study with 5 participants, it was estimated that people are usually able to make this decision within 5 minute on average. Thus, we introduced the time limitation of 3 minutes in making the nursing home selection decision. The time clock was shown in the top left corner of the screen. Another rationale behind this artificial time pressure is to cut down the total amount of time participants spent completing this experiment. Since the whole experiment consists of four different trials, participants may drop out of the experiment in the middle of following trials if the first trial takes too long. Due to the nature of web-based experiments, dropping out of an experiment is very difficult to control, so it was hoped that limiting the completion time would actually motivate a higher completion rate for the experiment. More specifically, at the outset of the experiment, an estimated time to complete the experiment (about 30 minutes) was presented on the introduction page of the website.

A timer, which showed the remaining time for a trial, was visible throughout the whole trial, as shown in Figure 29. It was intentionally designed that way, so that it does not block the region of visual interaction. However, it was designed to provide enough visual feedback though bigger font size and distinctive colors. If the remaining time was less than 30 seconds, the color of the timer is changed to red, so that it became more noticeable. After each trial, the time pressure that a participant experienced was measured as well.

Decision quality was also measured through the actual choice that a participant made and the post-trial survey. The accuracy of the decision was assessed in terms of the relative weighted additive utility of each choice (Lurie 2004), and the preference structure of each participant was captured through a post-task survey:

$$\text{Decision Accuracy} = \frac{WeightedAdditiveValue_{Choice} - WeightedAdditiveValue_{Worst}}{WeightedAdditiveValue_{Best} - WeightedAdditiveValue_{Worst}}$$

In addition, after each trial, the following six questions were asked to measure the level of satisfaction, confidence, and confusion experienced by the participant during the decision making process with seven point Likert scales. These questions were adapted from Agnew and Szykman's survey (2005), and the author added a question asking the level of time pressure. The list of questions and corresponding variable names were shown in Table 31.

Table 31. Questions to measure subjective decision quality

Questions	Possible responses (7-point Likert scale)	Variable names
How satisfied are you with your choice?	Very dissatisfied (1) - Very satisfied (7)	Satisfaction
How certain are you that you made the best choice?	Very uncertain (1) - Very certain (7)	Certainty
How confused did you feel while performing the task?	Very confused (1) - Not at all confused (7)	Confusion
How likely is it that you did NOT make the best choice?	Very likely (1) - Very unlikely (7)	BestChoice
How likely is it that some of the choices that you did NOT choose would be equal to or better than the ones that you did choose?	Very likely (1) - Very unlikely (7)	OtherGoodChoices
How much time pressure did you experience?	Very high (1) - Very low (7)	TimePressure

In the post-task survey, the following questions with seven-point Likert scales were asked to measure the usability that participants perceived. The questions were adapted from (Lewis 2002):

- Perceived ease of use
    - Learning to use this tool was easy: strongly disagree – strongly agree
    - Becoming skillful at using the tool was easy: strongly disagree – strongly agree
- Perceived usefulness
    - Using the tool would improve my performance in choosing a nursing home: strongly disagree – strongly agree
    - Using the tool in choosing a nursing home would increase my productivity: strongly disagree – strongly agree
    - Using the tool would enhance my effectiveness in choosing a nursing home: strongly disagree – strongly agree
    - I would find the tool useful in choosing a nursing home: strongly disagree – strongly agree
- Intensity of flow (involvement)
    - I thought about other things: strongly disagree – strongly agree
    - I had to make an effort to keep my mind on the activity: strongly disagree – strongly agree
    - I was aware of distractions: strongly disagree – strongly agree
- Intensity of flow (control)
    - Time seemed to pass quickly: strongly disagree – strongly agree

    - I knew the right things to do: strongly disagree – strongly agree
    - I felt like I received a lot of direct feedback: strongly disagree – strongly agree
    - I felt in control of myself: strongly disagree – strongly agree
- Aesthetic quality
    - I judge the tool to be: very complex – very simple
    - I judge the tool to be: very illegible – very legible
    - I judge the tool to be: very disordered – very ordered
    - I judge the tool to be: very ugly – very beautiful
    - I judge the tool to be: very meaningless – very meaningful
    - I judge the tool to be: very incomprehensible – very comprehensible
    - I judge the tool to be: very bad – very good

5.4 Results

5.4.1 Effects of Visualization Techniques

Table 32 shows the main effects of the visualization techniques on decision quality. Even though some measures of decision quality (i.e., Satisfaction, Certainty, Confusion, BestChoice, OtherGoodChoices, and TimePressure) are ordinal, not interval, the univariate ANOVA method was employed to analyze the data since using ANOVA to analyze rating scores of behaviors or conditions is common in social science (Munzel and Bandelow 1998; Gould 2002; Shah and Madden 2004). As shown in the table, the presence of CV affects decision accuracy ($F(1, 105) = 9.174$, $p < 0.01$) and the perception of confusion ($F(1, 105) = 4.046$, $p < 0.05$) while the presence of NCV did not affect any of the measures. No statistically significant interaction effects were observed.

Table 32. The effects of visualization techniques (CV and NCV) on decision quality

Factors	Measures	Type III Sum of Squares	df	Mean Square	F	Sig.
CV	Accuracy	1.707	1	1.707	9.174	**.003**
	TimeSpent	660454450.570	1	660454450.570	.109	.741
	Satisfaction	19.213	1	19.213	3.872	.052
	Certainty	22.192	1	22.192	3.314	.072
	Confusion	36.488	1	36.488	4.046	**.047**
	BestChoice	27.210	1	27.210	3.900	.051
	OtherGoodChoices	12.246	1	12.246	1.666	.200
	TimePressure	3.623	1	3.623	.325	.570
NCV	Accuracy	.667	1	.667	3.585	.061
	TimeSpent	4599316715.570	1	4599316715.570	.762	.385
	Satisfaction	8.898	1	8.898	1.793	.183
	Certainty	4.288	1	4.288	.640	.425
	Confusion	1.002	1	1.002	.111	.740
	BestChoice	5.12E-006	1	5.12E-006	.000	.999
	OtherGoodChoices	2.850	1	2.850	.388	.535
	TimePressure	8.390	1	8.390	.752	.388
CV * NCV	Accuracy	.068	1	.068	.365	.547
	TimeSpent	11035019546.080	1	11035019546.080	1.829	.179
	Satisfaction	.958	1	.958	.193	.661
	Certainty	.237	1	.237	.035	.851
	Confusion	14.713	1	14.713	1.632	.204
	BestChoice	.257	1	.257	.037	.848
	OtherGoodChoices	4.272	1	4.272	.581	.448
	TimePressure	2.029	1	2.029	.182	.671
Error	Accuracy	19.538	105	.186		
	TimeSpent	633428851218.777	105	6032655725.893		
	Satisfaction	520.974	105	4.962		
	Certainty	703.124	105	6.696		
	Confusion	946.892	105	9.018		
	BestChoice	732.631	105	6.977		
	OtherGoodChoices	771.611	105	7.349		
	TimePressure	1172.114	105	11.163		

Tables 32 and 33 show that the presence of CV actually lowered decision accuracy and increase the confusion.

Table 33. Estimated marginal means of decision quality when CV is absent and present

Measures	CV	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Accuracy	Absent	.835	.028	.779	.891
	Present	.709	.031	.648	.770
TimeSpent	Absent	79906.611	5056.624	69880.259	89932.962
	Present	77426.720	5532.086	66457.615	88395.824
Satisfaction	Absent	5.455	.145	5.167	5.743
	Present	5.032	.159	4.717	5.347
Certainty	Absent	5.010	.168	4.676	5.344
	Present	4.555	.184	4.190	4.921
Confusion	Absent	4.930	.196	4.542	5.318
	Present	4.347	.214	3.923	4.771
BestChoice	Absent	4.550	.172	4.209	4.891
	Present	4.047	.188	3.674	4.420
OtherGoodChoices	Absent	4.060	.176	3.711	4.410
	Present	3.723	.193	3.340	4.106
TimePressure	Absent	3.950	.218	3.519	4.381
	Present	4.134	.238	3.662	4.605

Table 34. Estimated marginal means of decision quality when NCV is absent and present

Measures	NCV	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Accuracy	Absent	.811	.029	.755	.868
	Present	.733	.030	.673	.793
TimeSpent	Absent	75394.556	5144.625	65193.715	85595.396
	Present	81938.775	5450.345	71131.748	92745.802
Satisfaction	Absent	5.387	.148	5.095	5.680
	Present	5.100	.156	4.790	5.410
Certainty	Absent	4.882	.171	4.543	5.222
	Present	4.683	.182	4.323	5.043
Confusion	Absent	4.687	.199	4.292	5.081
	Present	4.590	.211	4.172	5.008
BestChoice	Absent	4.299	.175	3.952	4.646
	Present	4.299	.185	3.931	4.666
OtherGoodChoices	Absent	3.810	.180	3.454	4.166
	Present	3.973	.190	3.596	4.350
TimePressure	Absent	3.902	.221	3.463	4.341
	Present	4.181	.234	3.717	4.646

As shown in Table 35, the result of the univariate ANOVA test with usability surveys also illustrated that the tool with CV was more difficult to learn ($F(1,111) = 9.627$, $p < 0.05$), less useful in choosing a nursing home ($F(1,111) = 6.230$, $p < 0.05$), more disordered ($F(1,111) = 6.126$, $p < 0.05$), bad ($F(1,111) = 7.692$, $p < 0.05$), more illegible ($F(1,111) = 10.412$, $p < 0.05$), more incomprehensible($F(1,111)=7.810$, $p < 0.05$), and more ugly ($F(1,111) = 4.655$, $p < 0.05$) than the tool without CV. Table 36 shows that the tool with NCV was more difficult learn ($F(1,111) =5.826$, $p < 0.05$), more distracting ($F(1,111) = 4.110$, $p<0.05$), less engaged ($F(1,111)=6.608$, $p < 0.05$), more disordered ($F(1,111)=4.390$, $p < 0.05$), and less meaningful ($F(1,111)=4.263$, $p < 0.05$). There were no interaction effects between CV and NCV on the results of usability surveys.

Table 35. The results of univariate ANOVA regarding usablity when CV is absent and present

Measures		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Learning to use this tool was easy.	Contrast	31.235	1	31.235	9.627	**.002**
	Error	360.128	111	3.244		
Becoming skillful at using the tool was easy.	Contrast	10.502	1	10.502	3.338	.070
	Error	349.255	111	3.146		
Using the tool would improve my performance in choosing a nursing home.	Contrast	7.179	1	7.179	3.351	.070
	Error	237.794	111	2.142		
Using the tool would enhance my effectiveness in choosing a nursing home.	Contrast	6.154	1	6.154	2.876	.093
	Error	237.534	111	2.140		
I would find the tool useful in choosing a nursing home.	Contrast	12.266	1	12.266	6.230	**.014**
	Error	218.542	111	1.969		
I thought about other things.	Contrast	9.242	1	9.242	3.244	.074
	Error	316.219	111	2.849		
I had to make an effort to keep my mind on the activity.	Contrast	11.499	1	11.499	3.430	.067
	Error	372.069	111	3.352		
I was aware of distractions.	Contrast	7.629	1	7.629	2.890	.092
	Error	293.013	111	2.640		
Time seemed to pass quickly.	Contrast	5.638	1	5.638	1.992	.161
	Error	314.175	111	2.830		
I knew the right things to do.	Contrast	1.212	1	1.212	.455	.501
	Error	295.461	111	2.662		
I felt like I received a lot of direct feedback.	Contrast	7.761	1	7.761	2.327	.130
	Error	370.130	111	3.335		
I felt in control of myself.	Contrast	3.136	1	3.136	1.174	.281
	Error	296.511	111	2.671		
Aesthetic quality: complex - simple	Contrast	7.317	1	7.317	2.209	.140
	Error	367.687	111	3.312		
Aesthetic quality: disordered - ordered	Contrast	12.022	1	12.022	6.126	**.015**
	Error	217.853	111	1.963		
Aesthetic quality: bad - good	Contrast	10.821	1	10.821	7.692	**.007**
	Error	156.159	111	1.407		
Aesthetic quality: illegible - legible	Contrast	23.030	1	23.030	10.412	**.002**
	Error	245.520	111	2.212		
Aesthetic quality: incomprehensible - comprehensible	Contrast	12.114	1	12.114	7.810	**.006**
	Error	172.170	111	1.551		
Aesthetic quality: meaningless - meaningful	Contrast	3.275	1	3.275	2.201	.141
	Error	165.215	111	1.488		
Aesthetic quality: ugly - beautiful	Contrast	8.541	1	8.541	4.655	**.033**
	Error	203.638	111	1.835		

Table 36. The results of univariate ANOVA regarding usablity when NCV is absent and present

Measures		Sum of Squares	df	Mean Square	F	Sig.
Learning to use this tool was easy.	Contrast	18.903	1	18.903	5.826	**.017**
	Error	360.128	111	3.244		
Becoming skillful at using the tool was easy.	Contrast	1.665	1	1.665	.529	.468
	Error	349.255	111	3.146		
Using the tool would improve my performance in choosing a nursing home.	Contrast	6.260	1	6.260	2.922	.090
	Error	237.794	111	2.142		
Using the tool would enhance my effectiveness in choosing a nursing home.	Contrast	5.305	1	5.305	2.479	.118
	Error	237.534	111	2.140		
I would find the tool useful in choosing a nursing home.	Contrast	4.343	1	4.343	2.206	.140
	Error	218.542	111	1.969		
I thought about other things.	Contrast	1.605	1	1.605	.564	.454
	Error	316.219	111	2.849		
I had to make an effort to keep my mind on the activity.	Contrast	12.733	1	12.733	3.799	.054
	Error	372.069	111	3.352		
I was aware of distractions.	Contrast	10.850	1	10.850	4.110	**.045**
	Error	293.013	111	2.640		
Time seemed to pass quickly.	Contrast	18.703	1	18.703	6.608	**.011**
	Error	314.175	111	2.830		
I knew the right things to do.	Contrast	8.259	1	8.259	3.103	.081
	Error	295.461	111	2.662		
I felt like I received a lot of direct feedback.	Contrast	.016	1	.016	.005	.945
	Error	370.130	111	3.335		
I felt in control of myself.	Contrast	2.006	1	2.006	.751	.388
	Error	296.511	111	2.671		
Aesthetic quality: complex - simple	Contrast	4.722	1	4.722	1.426	.235
	Error	367.687	111	3.312		
Aesthetic quality: disordered - ordered	Contrast	8.617	1	8.617	4.390	**.038**
	Error	217.853	111	1.963		
Aesthetic quality: bad - good	Contrast	1.350	1	1.350	.960	.329
	Error	156.159	111	1.407		
Aesthetic quality: illegible - legible	Contrast	2.046	1	2.046	.925	.338
	Error	245.520	111	2.212		
Aesthetic quality: incomprehensible - comprehensible	Contrast	4.253	1	4.253	2.742	.101
	Error	172.170	111	1.551		
Aesthetic quality: meaningless - meaningful	Contrast	6.345	1	6.345	4.263	**.041**
	Error	165.215	111	1.488		
Aesthetic quality: ugly - beautiful	Contrast	1.760	1	1.760	.960	.329
	Error	203.638	111	1.835		

Table 37. The means of usability survey scores in the four different conditions

Measures	Both	CV	NCV	None	Total
Learning to use this tool was easy.	3.91 Neutral	4.73 Somewhat agree	4.97 Somewhat agree	5.78 Agree	4.92 Somewhat agree
Becoming skillful at using the tool was easy.	4.30 Neutral	4.43 Neutral	4.80 Somewhat agree	5.16 Somewhat agree	4.70 Somewhat agree
Using the tool would improve my performance in choosing a nursing home.	4.87 Somewhat agree	5.30 Somewhat agree	5.33 Somewhat agree	5.84 Agree	5.37 Somewhat agree
Using the tool would enhance my effectiveness in choosing a nursing home.	4.91 Somewhat agree	5.43 Somewhat agree	5.47 Somewhat agree	5.81 Agree	5.44 Somewhat agree
I would find the tool useful in choosing a nursing home.	5.04 Somewhat agree	5.23 Somewhat agree	5.50 Agree	6.09 Agree	5.50 Agree
I thought about other things.	3.43 Somewhat disagree	2.93 Somewhat disagree	2.60 Somewhat disagree	2.63 Somewhat disagree	2.86 Somewhat disagree
I had to make an effort to keep my mind on the activity.	3.65 Neutral	2.83 Somewhat disagree	2.87 Somewhat disagree	2.34 Disagree	2.87 Somewhat disagree
I was aware of distractions.	3.83 Neutral	2.63 Somewhat disagree	2.73 Somewhat disagree	2.69 Somewhat disagree	2.91 Somewhat disagree
Time seemed to pass quickly.	4.52 Somewhat agree	5.50 Agree	5.13 Somewhat agree	5.78 Agree	5.29 Somewhat agree
I knew the right things to do.	4.57 Somewhat agree	4.87 Somewhat agree	4.53 Somewhat agree	5.31 Somewhat agree	4.84 Somewhat agree
I felt like I received a lot of direct feedback.	3.61 Neutral	3.87 Neutral	4.37 Neutral	4.16 Neutral	4.03 Neutral
I felt in control of myself.	4.87 Somewhat agree	4.97 Somewhat agree	5.03 Somewhat agree	5.47 Somewhat agree	5.10 Somewhat agree
Aesthetic quality: complex - simple	3.74 Neutral	4.17 Neutral	4.27 Neutral	4.66 Somewhat simple	4.24 Neutral
Aesthetic quality: disordered - ordered	4.61 Somewhat ordered	5.30 Somewhat ordered	5.40 Somewhat ordered	5.81 Ordered	5.33 Somewhat ordered
Aesthetic quality: bad - good	4.91 Somewhat good	5.23 Somewhat good	5.63 Good	5.75 Good	5.42 Somewhat good
Aesthetic quality: illegible - legible	4.39 Neutral	4.97 Somewhat legible	5.60 Legible	5.56 Legible	5.18 Somewhat legible
Aesthetic quality: incomprehensible - comprehensible	4.74 Somewhat comprehensible	5.20 Somewhat comprehensible	5.47 Somewhat comprehensible	5.78 Comprehensible	5.34 Somewhat comprehensible
Aesthetic quality: meaningless - meaningful	5.22 Somewhat meaningful	5.77 Meaningful	5.63 Meaningful	6.03 Meaningful	5.70 Meaningful
Aesthetic quality: ugly - beautiful	3.83 Neutral	4.13 Neutral	4.43 Neutral	4.63 Somewhat beautiful	4.29 Neutral

5.4.2 Effects of the Amount of Information

Changes in the amount of information showed statistically significant differences of several decision quality measures. More attributes ("wide") made participants less accurate ($F(1,105)=8.333$, $p < 0.01$), spend more time ($F(1,105)=14.922$, $p < 0.01$), be less certain ($F(1,105)=11.665$, $p < 0.01$), more confused ($F(1,105)=6.908$, $p < 0.05$), more prone to think that other better choices exist ($F(1,105)=8.721$, $p<0.01$), less satisfied ($F(1,105)=11.960$, $p < 0.01$), and experience more time pressure ($F(1,105)=8.470$, $p < 0.01$). Thus, presenting more attributes clearly degraded the overall decision quality. More alternatives ("long") also made participants spend more time ($F(1,105)=8.125$, $p < 0.01$) and feel more time pressure ($F(1,105)=5.779$, $p < 0.01$). However, other decision quality measures did not show any statistically significant differences. No interaction effects between width (i.e., the number of attributed presented) and height (i.e., the number of alternatives presented) were observed.

Table 38. The effects of the amount of information (Width and Height) on decision quality

Factors	Measures	Type III Sum of Squares	df	Mean Square	F	Sig.
Width	Accuracy	.295	1	.295	8.333	**.005**
	BestChoice	4.913	1	4.913	3.530	.063
	Certainty	15.129	1	15.129	11.665	**.001**
	Confusion	7.949	1	7.949	6.908	**.010**
	OtherGoodChoices	12.132	1	12.132	8.721	**.004**
	Satisfaction	12.058	1	12.058	11.960	**.001**
	TimePressure	15.130	1	15.130	8.470	**.004**
	TimeSpent	18501962030.235	1	18501962030.235	14.922	**.000**
Height	Accuracy	.092	1	.092	3.161	.078
	BestChoice	4.007	1	4.007	3.899	.051
	Certainty	1.000	1	1.000	.977	.325
	Confusion	1.253	1	1.253	1.521	.220
	OtherGoodChoices	3.216	1	3.216	2.820	.096
	Satisfaction	1.268	1	1.268	1.444	.232
	TimePressure	5.908	1	5.908	5.779	**.018**
	TimeSpent	8973907174.105	1	8973907174.105	8.125	**.005**
Width * Height	Accuracy	.053	1	.053	1.309	.255
	BestChoice	.151	1	.151	.148	.701
	Certainty	.009	1	.009	.008	.927
	Confusion	.550	1	.550	.493	.484
	OtherGoodChoices	.448	1	.448	.503	.480
	Satisfaction	.011	1	.011	.014	.905
	TimePressure	.009	1	.009	.008	.930
	TimeSpent	37244651.223	1	37244651.223	.041	.840
Error	Accuracy	19.538	105	.186		
	TimeSpent	633428851218.777	105	6032655725.893		
	Satisfaction	520.974	105	4.962		
	Certainty	703.124	105	6.696		
	Confusion	946.892	105	9.018		
	BestChoice	732.631	105	6.977		
	OtherGoodChoices	771.611	105	7.349		
	TimePressure	1172.114	105	11.163		

Table 39. Estimated marginal means of decision quality when width is wide and narrow

Measures	width	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Accuracy	wide	.746	.023	.700	.792
	narrow	.798	.022	.754	.842
TimeSpent	wide	85229.479	4302.623	76698.171	93760.786
	narrow	72103.852	3917.521	64336.131	79871.572
Satisfaction	wide	5.076	.125	4.828	5.324
	narrow	5.411	.110	5.193	5.629
Certainty	wide	4.595	.144	4.309	4.881
	narrow	4.970	.128	4.716	5.224
Confusion	wide	4.502	.160	4.186	4.819
	narrow	4.774	.148	4.481	5.067
BestChoice	wide	4.192	.142	3.911	4.473
	narrow	4.406	.137	4.133	4.678
OtherGoodChoices	wide	3.724	.149	3.428	4.020
	narrow	4.060	.136	3.791	4.329
TimePressure	wide	3.854	.179	3.500	4.208
	narrow	4.229	.169	3.895	4.564

Table 40. Estimated marginal means of decision quality when height is long and short

Measures	height	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Accuracy	long	.757	.023	.711	.804
	short	.787	.021	.744	.829
TimeSpent	long	83237.252	4332.972	74645.769	91828.735
	short	74096.078	3801.840	66557.733	81634.424
Satisfaction	long	5.189	.124	4.944	5.434
	short	5.298	.109	5.082	5.514
Certainty	long	4.734	.140	4.456	5.013
	short	4.831	.127	4.578	5.083
Confusion	long	4.584	.149	4.288	4.881
	short	4.692	.153	4.388	4.996
BestChoice	long	4.202	.143	3.918	4.486
	short	4.395	.129	4.139	4.652
OtherGoodChoices	long	3.805	.147	3.514	4.096
	short	3.978	.134	3.712	4.244
TimePressure	long	3.924	.172	3.584	4.265
	short	4.159	.165	3.831	4.486

5.4.3 User Comments

At the end of the post-task survey, participants were asked to list the most useful features, the least useful features, the features to change or remove, and any features they felt should be added through open-end questions. Participants' answers vary, but are codified and summarized in the following tables.

Table 41 summarizes the most useful features identified by participants. As shown in the table, basic features, such as "data itself," "sort", and "one page / spreadsheet," were frequently mentioned as the most useful features. Participants seemed to be very satisfied with having the quantitative quality information of nursing homes presented in a familiar spread sheet view on one screen. For example, a participant wrote "I like that the problems were categorized and by scrolling over the columns I could see what was what in case I needed to check again," and another wrote, "Being able to check how the nursing home ranked for each factor separately." In addition, another wrote that the sorting feature was very useful by saying "the ability to sort from lowest to highest - this made my choice much easier."

However, some unconventional features such as the weighting slider bar with the summation column, the distribution view, and bar graphs were also mentioned as useful features by several participants. For example, one participant mentioned "Being able to set how important each feature of a nursing home was to me, as well as the SUM column" is the most important feature, and another mentioned, "the sum scores given made it easier to narrow it down." In spite of the complexity and novelty, the distribution view was also mentioned as a very useful feature. For example, one individual wrote, "the distribution tool was useful comparatively to gauge where you stood in terms of other homes with this feature." These results showed that these relatively new visualization techniques were accepted by some participants even though they were exposed to these features over a short time period.

Some other features such as turn on/off bar graphs and/or numbers, remove rows, zoom in/out, and highlight were also listed as the most useful features. However, these were relatively rare opinions.

Table 41. The most useful features

The most useful features	Counts
Data itself	29
Sort	22
The weighting feature (slider bar + the "SUM" column) (CV)	18
The distribution view (NCV)	16
Bar graph	10
One page / spreadsheet	10
Description	5
Turn on/off bar graph and/or number	3
Remove rows	3
Zoom in/out	3
Highlight	2

Interestingly, when asked about the least useful features, the most frequent answer was the "zoom in/out" feature, as identified by 29 participants. Some comments from participants showed why they did not like the zoom in/out features: "The zoom in / zoom out button made it hard to read;" "Zoom out. It made it impossible to read." This feature was added to provide the participants with the ability to switch between the overview and the detailed view of data points. However, when the screen was zoomed out, the bar charts were shrunk and the numbers on bar charts were disappeared due to a lack of spaces for numbers. Participants appeared not to like to lose the detailed numbers and nursing home names.

The second most frequent answer for the least useful feature was the weighting feature. The reasons why the weighting feature was perceived as the least useful were not clear in the nine comments. One participant wrote, “The summary since it really didn't tell me anything,” which suggests that the “SUM” column might be difficult to understand. Compared with the weighting feature, the distribution feature was not listed as the least useful feature. Only two participants mentioned that the distribution feature was the least useful.

Another difficulty that participants reported was information overload. A total of eight participants mentioned that the tool has too much information, too many attributes, or too much description (“definition of each abbreviation was too long” and “Having the explanation of each category - just bed sores would suffice”).

Besides these issues, five participants mentioned that the “Turn on/off bar graphs and/or numbers” feature was not useful. Four participants also mentioned that the abbreviations were too cryptic. One wrote, “It is also difficult to remember the various abbreviations at the tops of the columns.”

Table 42. The least useful features

The least useful features	Counts
Zoom in/out	23
The weighting feature (slider bar + the "SUM" column) (CV)	9
Turn on/off bar graphs and/or numbers	5
Abbreviations	4
The normal view	3
Too many attributes	3
Too much information	3
Bar graph	2
The distribution (NCV)	2
Sort	2
Time limit	2
Too much description	2
Everything (too confusing)	1
Numbers	1
Remove rows	1
One page / spreadsheet	1
Too small print	1

When asked about potential features to add, participants provided several suggestions, as summarized in Table 43. The most dominant suggestion was adding more attributes, despite the fact that several participants complained about the presence of too many attributes already. However, 18 participants mentioned that they would have liked some additional attributes, such as complaints and/or misconduct reported to each nursing home, resident-to-staff ratio, food quality, physical therapy quality, location / proximity, patients' rating, the change of health conditions, and the patient capacity. In order to add all of these different attributes, the tool should have another feature to add and remove attributes easily. Actually, two participants had asked for the "adding and remove attributes" feature.

The next frequently asked for feature was the ability to set aside the most competitive nursing homes to take a closer look or compare them side-by-side. Even though the current tool already provided a visual presentation that allows comparison between multiple options, participants appeared to wanted the ability to set aside a smaller set of candidates for the further investigation.

Seven participants who used the tool without CV asked for the weight feature. Interestingly, three of them described the feature as a "multi-column sorting" feature. For example, "Sort by more than one category i.e. Sort by Column a, then by e, the by c as you can in Excel." The notion of multi-column sort appears to be well-understood by some of participants probably because the feature is well implemented in popular applications such as Microsoft Excel. Thus, borrowing the notion of multi-column sorting might help future users better understand this feature. However, the difference between "multi-column sorting" and "weighted sorting" should be noted. When values in column A have no ties, multi-column sorting by column A, B, and C and single-column sorting by column A will arrange the data in the same way because secondary sorting (sorting by column B) only affects the sorting order when there are ties in column A. Thus, when the multi-column sorting feature is implemented in a decision supporting tool, the sorting algorithm should be implemented differently and carefully.

Some participants asked for features that were already implemented in the tool. Two participants asked for the sorting feature, two asked for the multiple highlight feature, and one asked for the filtering feature to remove some nursing homes based on some given criteria. Sorting can be used by clicking a column header, multiple highlighting can used by clicking on nursing homes with holding the SHIFT or CTRL keys, and filtering can be done by using the sorting feature with removing rows feature. These features appeared to be a bit difficult to find by some of participants, so these features should be designed to be easier to find and use in the future iteration of the tool.

Table 43. The features to add

The features to add	Counts
Add attributes	18
Ability to collect the most competitive nursing homes to take a closer look / side-by-side comparison	6
Automatic recommendation / ranking	5
The weight feature / the multi-column sorting feature / Summary scores	7
More information about each NH	3
Multiple highlight	2
Separate long stay and short stay	2
Sort	2
Ability to add/remove attributes	2
Ability to make notes	1
Cost analysis	1
Horizontal scroll bar	1
Keyboard navigation	1
Restore the removed rows	1
Show the description change any of the row, not only at the column header.	1
Text-based search	1
Filtering	1

Another open ended question asked in the post-task survey regarded features to remove or change. As shown in Table 44, many suggestions are pertinent to usability issues. Eight participants wanted to make cryptic abbreviations on column headers easier to interpret. One of them mentioned, “I would use a better way of labeling the conditions, instead of just using the 3 letters, it got a bit confusing.” Even though this is a fair suggestion, labeling the column headers with more descriptive and lengthy names will be challenging due the large number of attributes to display. One solution would be swapping columns and rows. In other words, each row represents an attribute, and each column represents a nursing home. This representation can provide more space for each attribute by sacrificing spaces for nursing homes. However, if there are many nursing homes to present, it may require the use of horizontal scrolling, which is often discouraged by many usability standards (e.g., http://www.useit.com/alertbox/20050711.html)

Seven participants wanted to have better and simpler instructions or video tutorials. One participant suggested to provide instruction regarding not only the features of the tool but also the general problems in choosing a nursing home by saying, "Many of the concepts here may not be understandable to a consumer of such services. Perhaps an introductory video on nursing homes and the types of ailments, symptomology, etc. would be helpful." Some participants prefer textual instruction to a video tutorial. One even suggested, "break the tutorial video into several pieces for easier reference."

Other participants suggested removing some unnecessary attributes in order to lower the amount of information by saying "Remove irrelevant columns. Ex. This was not to be a short term stay, so remove data on short term stays as not being especially relevant to this situation (knowing of course that treatment of patients in short term stay MAY indicate quality of care overall)." This is a fair suggestion, but a challenge in implementing the feature is how to identify which attributes are relevant in advance.

Table 44. The features to remove or change

The features to remove or change	Counts
Make abbreviation easier	8
Better/simple instruction	7
Fewer attributes	6
Remove the time limit	6
Bigger print	5
Bigger screen / full screen	5
Make it simpler / easier to understand	3
Remove zoom in/out	2
Color encoding	1
Improve aesthetics	1
Make highlights darker	1
Make the SUM column more meaningful	1
Remove the distribution feature	1
Show everything in one screen (without vertical scroll)	1

Finally, the survey asked for any general comments. Many left their general impressions about the tool. Their comments were categories into five different categories as shown in Table 45. As many participants did not leave their comments, and because the categorization is also subjective, the counts of positive and negative comments would fail to provide any scientifically testable arguments. However, some comments might show more clear perspectives of participants, so two fully positive comments and two fully negative comments were quoted as follows:

> "I enjoyed using the tool and the tutorial for using it was very easy to understand. The video was also easy to use. I thought that the time went by so quickly on the 1st experiment but by the 2nd one I got the hang of things and ignored the clock. Well done."

> "I like having info available about bedsores and restraints and pain control (and the other measures). I wish I had had access to this kind of info when I was choosing a nursing home for my mom."

> "It is really hard to check a nursing home out this way, because some might seem really great until a family member moves in. That is why I

visit every day to check on my family member, and I go at different times each day. The best way to get a feel of a nursing home when a family member moves in to watch and listen, a person can learn a lot about a nursing home that way. All I want is my loved one to have the care and the respect they deserve."

"Wow, this is a very confusing way of going about this sensitive subject. I do not like this at all, it gives me a bad feeling. When choosing something like a nursing home for a loved one this is not a very comfortable way to go about it. It feels way too formal and impersonable."

Table 45. Participants' comments

Comments	Counts
Fully positive	13
Partially positive	7
Neutral or no comments	81
Partially negative	10
Fully negative	4

5.5 Discussion

The overall decision quality and usability scores resulting from the web-based experiment were quite positive. Over 60% of valid participants (72 out of 115) participants made fairly accurate choices, implying that they chose one of the top 20% nursing homes through the four trials. Their perceived decision quality and usability scores were generally positive (3 out of 19 usability measures were neutral, and 16 out of 19 usability measures were slightly positive or positive). Since the target population of this study is relatively older than many human-computer interaction studies employing college students as a subject pool, the author believes that the results are generally positive.

However, when the details are examined, the benefits of the proposed visualization techniques are not evident. Decisions made by participants who used the tool with CV were less accurate and these participants rated that they felt more confusion while performing the task than participants who used the tool without CV. Decisions made by participants who used the tool with NCV were comparable with decisions made without NCV.

One explanation of these results is that users did not use the given techniques while making a decision. Table 46 shows the number of participants who utilized the given visualization techniques partially or fully. As shown in the table, when both CV and NCV were given, only 13% of participants fully utilized both of them throughout all of the four trials, and 34.8% of participants utilized both of them at least in one of the four conditions. Since participants did not utilize the given techniques even after watching the video tutorial, the results of decision quality did not show statistically significant differences.

Table 46. The number of participants who used the given visualization techniques

	Both	CV	NCV	None	Total
Valid participants	23	30	30	32	115
Participants who utilized the given visualization techniques at least in one of the four conditions (percentage)	8 (34.8%)	19 (63.3%)	19 (63.3%)	32 (100%)	78 (67.8%)
Participants who utilized the given visualization techniques in all of the four conditions (percentage)	3 (13.0%)	11 (36.7%)	11 (36.7%)	32 (100%)	57 (49.6%)

The lack of usage of the additional visualization techniques could be explained in two ways. One explanation is that the usability of these visualization techniques is poor, so the participants did not understand how to use these features and, thus, failed to use them. The other explanation is that the participants did not have enough time to utilize these techniques due to the three minute time limit. One participant's comment is in line with this explanation: “The limited time stressed me so much that I did not feel I learned how to use the tools enough to make an accurate decision.” For now, it is not clear which explanation is correct, and the follow-up interview study might provide more clues to this question.

However, the fact that many participants did not use the given visualization techniques cannot explain why the tool with CV introduced lower accuracy and more confusion. Figure 21 shows the scatter plots showing the relationship between the average accuracy and the average time spent. Figure 21 (a) is the scatter plot when CV was present, and Figure 21 (b) is the scatter plot when CV was absent. These two figures clearly show that the decision accuracies of participants who used the tool with CV were clearly degraded. However, one puzzling pattern is that some extremely inaccurate decisions can be found. Figure 21 (a) shows that the average accuracy of two participants is near zero, which implies that the two participants chose the near-worst choices among nursing homes. Similar participants were not observed in Figure 21 (b). Although the tool with CV is difficult to understand or use, choosing the worst nursing home among many nursing home is also very difficult.

A participant’s comment may provide a hint to this puzzle: One wrote, “I think it should have at the top if the higher sum is better or the lower sum is. I got confused with that.” In the CV condition, a participant saw a special column, called the “SUM” column, as described in previous chapter. As explained in the video tutorial, “the SUM column contains the weighted summary of all columns. So, if the value of the SUM column is small, it means that the overall risk of the nursing home is small.” (Please refer to Appendix D for the full narration of the video tutorial.) However, for some reason, some participants, including the one who left the comment above, appeared to be confused that the higher value is better, and chose the worst nursing homes. The next version of the tool should be clearer about this matter.

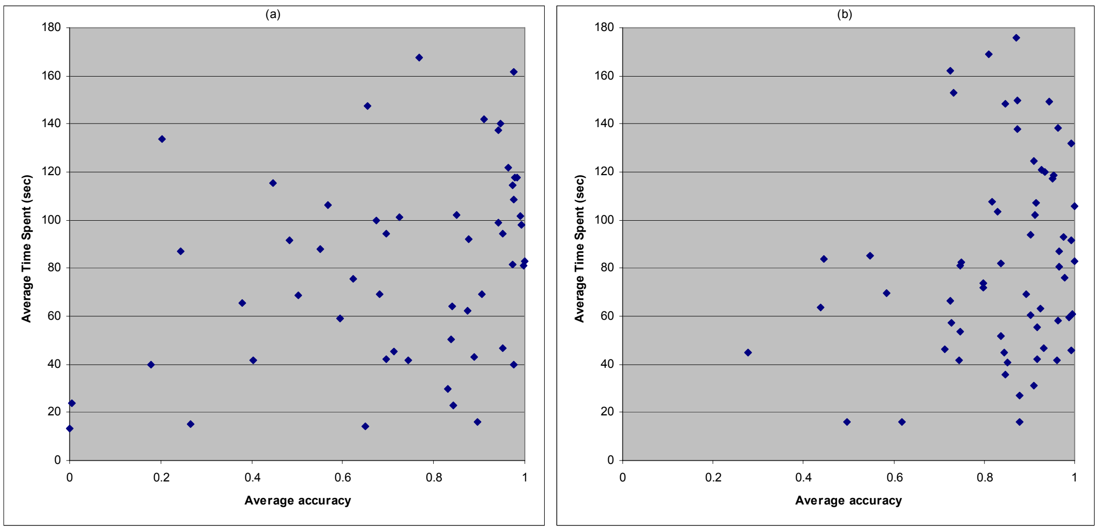

Figure 21. The scatter plots of accuracy and time spent when CV was present (a) and absent (b)

The effects of the amount of information were clear. The long condition made participants spend more time and feel more time pressure, but did not lower participants' other perceived decision quality (i.e., Accuracy, Satisfaction, Certainty, Confusion, OtherGoodChoices, and Satisfaction). However, the wide condition lowered decision quality in every measure except for BestChoice. This result shows that the number of attributes presented is a more influencing factor to the decision quality than the number of alternatives presented. Presenting more alternatives simply causes more individuals to spend more time sorting through these choices. However, presenting more attributes not only causes individuals to spend more time, but also degrades various decision quality. This quantitative result is in line with some participants' suggestion of presenting fewer attributes.

According to the results of the statistical analysis, the best combination of the tool would be the tool without either CV or NCV. The number of attributes should be also minimized if possible. However, the number of alternatives does have a significant impact.

However, CV and NCV should not be permanently discarded. As shown in participants' comments, some of participants found that CV and NCV were the most useful features. For those who understand how to use these interactive features properly, they might save time and energy to make better decisions.

CHAPTER 6: FOLLOW-UP INTERVIEWS

6.1 Purposes

The purpose of the follow-up interviews is to better understand how participants utilized VDM under the different experimental conditions. Although several quantitative and qualitative data were collected in the web-based experiment, the collected information is of limited utility for understanding the underlying cognitive processes of participants during their decision making processes. Thus, an interview study with some of participants was conducted.

More specifically, the study was designed to answer the following questions: 1) What are the overall impressions of participants? 2) What kinds of difficulties did participants experience during the experiment? 3) What kinds of strategies did participants use? and 4) How did the given visualization techniques support or impede participants' strategies?

6.2 Methods

6.2.1 Participants

Eleven participants were recruited for this interview. Eight were participants of the web-based experiment, and three were participants in the interview study in the requirements analysis. The former eight were recruited by email that was sent to the 85 volunteers who expressed their interest in the follow-up interview while completing the web-based experiment. Out of 85 volunteers, 31 people signed up for interviews, and eight were eventually interviewed. As participants were often remotely located, all of the interviews were conducted over the phone. A problem with the phone interview was that the interviewer cannot observe how interviewees used VDM. In order to overcome the limitations, the latter three participants, who were locally located, were interviewed, and how they used VDM was directly observed.

While selecting the eight interviewees out of 31 who responded to the email, the author paid close attention to include interviewees who experienced different visualization techniques and had both positive and negative opinions about VDM and the experiment. Please note that the additional three participants had not participated in the web-based experiment, but were informed of the link to VDM a week prior to the interviews and had time to try the tool in advance. Table 47 lists the interviewees and their experimental conditions and opinions about the tool. Please note that only one participant who experienced the CV condition was interviewed. Another interviewee with the same condition was scheduled, but the interviewee did not respond to the author's phone calls.

Table 47. The list of interviewees in the follow-up interviews

ID	Gender	Age	Prior studies participated	The experimental conditions	Opinions / attitude
P1	N/A	36	Web-based experiment	NCV	Positive
P2	Female	24	Web-based experiment	None	Positive
P3	Female	63	Web-based experiment	NCV	Negative
P4	Female	30	Web-based experiment	CV	Negative
P5	Female	49	Web-based experiment	None	Positive
P6	Female	40	Web-based experiment	None	Negative
P7	Female	55	Web-based experiment	Both	Positive
P8	Female	28	Web-based experiment	Both	Negative
P9	Male	61	Requirements analysis	-	-
P10	Female	59	Requirements analysis	-	-
P11	Male	51	Requirements analysis	-	-

Since these individuals passed the screening criteria in previous studies, they automatically met the following qualifications: 1) experience in researching and selecting a skilled nursing facility or nursing home in the past two (2) years; or anticipate a need to research and select a nursing home within the next five (5) years; 2) fluency in English and the ability to describe the experience of choosing a nursing home; 3) ability to utilize a personal computer and the Internet to perform research, online shopping, or similar tasks; and 4) normal or corrected-to-normal vision (i.e., sufficient vision for computer usage). The participants were compensated for their time and effort with gift certificates worth $20.

6.2.2 Procedure

At the outset of the interview, participants were asked to sign an informed consent form. In the case of the phone interview, an empty consent form was sent to the participant via email, and the participant was asked to fill it out and send back to the interviewer. Interview questions were generally pertinent to the four previously-mentioned research questions, but the interviewer allowed interviewees to freely talk about their impressions and experiences regarding VDM and their own nursing home choices. In the case of the face-to-face interviews, participants were encouraged to demonstrate, using a notebook computer, how they used VDM.

Each interview took thirty minutes to an hour, and the flow of the interview generally followed the prepared questions. However, when an interviewee discussed issues not covered by the prepared questions, the interviewer did not intervene or stop the interviewee. Instead, the interviewer tried to fully capture those issues as long as the interview could be finished within the allotted time.

6.3 Results

The overall impressions of the eight participants were in line with their comments left in the surveys and their performance in the experiment except for P6, who was negative about VDM in the survey but became positive during the interview. As intended while selecting interviewees, their opinions showed clear contrast from one another. For example, P7 was very positive, “It was good. I wish that I had more time to figure out how to use it better. It was a very useful tool.” In contrast, P3 was very critical about VDM mainly because it provide only numerical information, which is not important to the participant. P3 said, “It was dull and tedious. It wasn't that easy to use. The same information is over and over again. It's all numbers, and it has no human side. It was very cumbersome and not easy to use. It has information that I didn't care. It was confusing, and it has no human touch. You want [your loved one] to be happy [in a nursing home]! You don't send a package [to a nursing home]." Among the local interviewees (i.e., P9, P10, and P11), two of them were positive about the tool, but the other one complained by saying “[It became] little more complicated [than the previous prototype I used]; it definitely requires more work. It's not intuitively obvious. It needs instruction.”

Nine interviewees except for P3 and P6 said that they did not have any problems in understanding the features of the tool. However, when they were asked about individual features, they did not remember or understand such features. In particular, five participants mentioned that the NCV feature, or the distribution feature, was difficult to understand. P9 said, “The ‘distribution’ is difficult in terms of its wording and the overall concept. People would not understand what ‘distribution’ is due to a lack of math knowledge.” P8 also disliked the feature because it totally changed the arrangement of nursing homes and confused her mental model. Besides the distribution feature, two participants reported that the zoom in / out feature was problematic. For example, P8 said, “I found it unnecessary. When zoomed out, it didn't show me enough information. Text was gone.” The other features than these two were fairly well understood by at least these eleven interviewees.

In order to understand how these features affect the decision making procedures, the interviewees were asked to describe how they chose the best nursing home in a step-by-step manner. Interestingly, though they had different sets of visualization techniques, they reported the following similar strategy:

1) Read through the description of all of the attributes on the screen.
2) Determine several attributes that are most important.
3) Select one attribute out of the important attributes.
4) Identify several nursing homes that have the lowest values in the selected attribute.
5) Set aside the identified nursing homes as good candidates.
6) Double check the good candidates; If one has unfavorable values in other attributes, then remove it from the set of good candidates.
7) Select another attribute out of the important attributes.
8) Go to Step 4.

Certainly, the fine details in the procedures used by individual interviewees vary. Before Step 1, P6 mentioned that she used the zoom out feature to see the overall trends to determine which attributes are more important. In Step 2, P7 mentioned that she used the weighing feature to mark which attributes are important. In Step 4, many interviewees reported that they used the sorting feature to identify the lowest values, but P2 reported that she just scrolled down and read through values even without bar graphs. In Step 5, several interviewees mentioned that they just mentally noted which nursing homes are good. However, P5 said that she used pencil and paper as her working memory, and P6 reported that she used the highlight feature to trace the good candidates.

One interesting finding is that none of eleven interviewees relied on the visualization techniques (i.e., the weighting and distribution features) to make their final decision even though these techniques were readily available and might be very helpful to alleviate some of the arduous cognitive tasks. Since P7 mentioned that she used the weighting feature to mark which attributes are important, the interviewer asked how she used the “SUM” column. P7 answered that she did not use it because it could be misleading. She said, “It [the ‘SUM’ column] can be misleading. Maybe a nursing home is good at something [some attribute], which is not important to me. Then, even though the ‘SUM’ looks good, it might not be good to me. It might be good to have, but I will not rely on.”

The distribution feature was not used by most of the interviewees. As describe previously, the distribution feature appeared to be a difficult concept to understand, and the name of the feature is also not familiar. P9 and P11 suggested other names such as “rankings,” “category ranking,” and “category ranking view.” P8 is the only interviewee who reported to use it, but she disliked it. She reported that the distribution feature rearranged everything, so she lost the track of good choices that she mentally noted. She said, “I remember that. It was confusing because when I clicked it, it threw you off. I knew that what was a good choice, but it messed up.” Another problem regarding the distribution feature is that it should be used with the zoom out feature. As shown in

Figure 22, when the zoomed-in view was used, and the first row of the "SUM" column is highlighted, highlights in other columns may not be shown. These highlights in other columns are outside of the view port, so you need to scroll down to see them. Then users cannot get the benefits of the distribution view. These hidden highlights can be seen if the zoomed-out view is used as shown in Figure 23. However, the zoomed-out view has another problem: It hides the detailed numbers, a fact which many participants dislike as previously discussed. In order to take advantage of the distribution view, this dilemma should be solved.

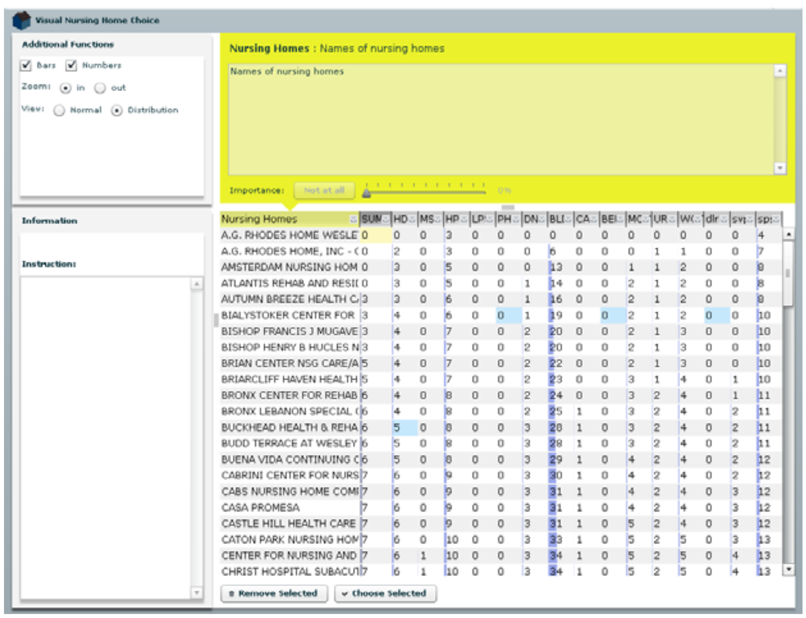

Figure 22. The zoomed-in distribution view

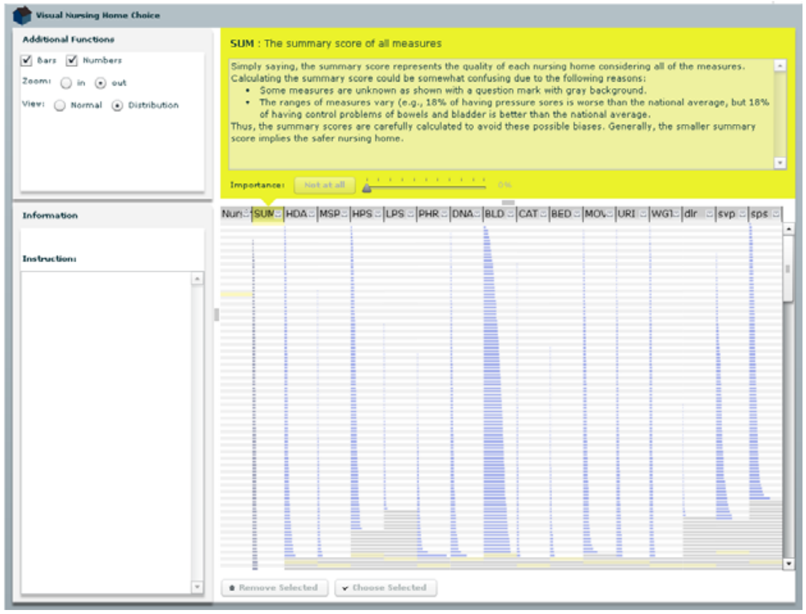

Figure 23. The zoomed-out distribution view

After learning that interviewees did not rely on these visualization techniques, the author was curious about how they could handle the trade-off situation, that is, one nursing home candidate with a lower risk in one attribute has a higher risk in another attribute. Most of the interviewees reported that they often encountered these situations and solved the issue using various heuristics. P6 used arbitrary criteria to judge whether a good candidate is worthwhile to keep or not. When she found a good choice that has a lower risk in a certain attribute, she read through values in other attributes. If any of values is higher than 20%, she discarded the candidate. The cut-off standard of 20% appeared to be arbitrary, but her rationale is following: If the 20% of its residents have any kind of problem, the nursing home has a problem. P5 used a slightly different heuristic. When she found a good candidate, she found the weakness of the nursing home. In other words, she looked for which attribute of the nursing home has the worst value, or the highest risk. If the attribute is not that important, she accepted it as a candidate. If not, she discarded it. P8 used a more complicated heuristic. She said, “If one is really good at one criterion, and really bad at another criterion, I mentally note that these two attributes are canceled out. I tried to mentally follow 5-6 options until I made the final decision.” The author believes that she mentally calculated the rough summation of different values.

The approaches that P1 and P2 employed were peculiar. P1 just focused on the two attributes and ignored other attributes, so he reported that he did not encounter any trade-off situations. The P2’s approach was slightly mysterious. P2 described her approach as follows, “1) Looked at the smallest numbers of NH for each column/acronym; 2) Just looked at the screen, not jotting down; 3) I experienced lots of trade-off. Some good options happen to have a large number, so I had to drop that option and move on to the next one; 4) Keep scrolling; 5) Graphs didn't help me too much, so I turned off the bar chart, and just looked at the numbers; 6) I didn't touch any of the buttons (e.g., Remove Selected); 7) I just focused on the four most important acronyms and ignore others.” According to the event log she left, she even did not use any of the features including the sorting feature. She simply read through the list. More surprisingly, she chose the best choices in all of the four trials.

The interviewer also asked the most and least useful features and the feature to add, remove, or change, which was summarized in Table 48. The list is not that different from what we found in the survey results of the web-based experiment.

Table 48. Features to add and remove/change

Features to add	Features to remove / change
More feature from Microsoft Excel (1)* More informative attributes (3) A feature to set aside good candidates (1) Virtual tours of nursing homes (1) The data of assisted living facilities A feature that allows users to enter the data directly (1) The state/nation-wide averages (2) The highlighting feature (this is already implemented) (1) A button to show the tutorial (1)	Break the video tutorial into multiple pieces (1) Remove Zoom-in/out feature (1) Change the abbreviations more meaningful Keep it simple (1) Remove the time limit (1)

* Note: The numbers in parentheses are the numbers of participants who mentioned the particular issues.

As discussed in the results of the survey, one participant appreciated the detailed nursing home quality information. P10 said, "I would look at comparisons. I never thought about this kind of detailed information before, so I will look at them. Previously, I just looked at cleanliness, order, friendliness of caregivers. But, I found that this kind of information would be very helpful. I was lucky to have reputations of nursing homes since I live in this area. However, the people who do not live this area would find this information very helpful."

6.4 Discussion

Based on these relatively quick follow-up interviews with eleven participants, the author can shed light on how participants made decisions and how they utilized the given interaction and visualization techniques of the tool.

At least among interviewed participants, the visualization techniques were not used as the main tool to make the final decision. CV and NCV appeared to have some usability issues. Both visualization techniques may be simply difficult to understand, or, given the time limit, they did not have enough time to test out all of the available features. However, some participants clearly understood how they worked, but they did not use them. For example, a participant used the weighting slider bar to mark the important attribute for herself, but she did not use the "SUM" column since she doubt the values of the "SUM" column correctly reflect her value structure. In the same line, the distribution view was not properly used since the zoom-out view, which helps fully utilize the distribution view, can hide the important numbers.

Interestingly, however, participants made fairly accurate choices without having these visualization techniques. Several strategies and heuristics discussed in the results section led to very accurate decision, and the satisfaction level of participants appeared to be high enough. They complained about a lack of data and other issues, but they did not request any particular features like the weighting slider bar or the distribution view.

Based on these results, the two different directions of improvement were found. One direction was improving some usability issues in the visualization techniques. For the weighting slider bar, participants appeared to have some difficulties how the "SUM" value was calculated even after watching the video tutorial. More intuitive way to present the "SUM" value should be devised. One possible way to do is using a stacked histogram to present the "SUM" value to show the detailed composition of the "SUM" value. For the distribution view, the term to describe the feature should be change to something easy to understand. In addition, in order to show the detailed values while using zoomed-out view, the fish-eye technique can be used, so that values of a highlighted nursing home are enlarged and showing the values.

The other direction was focusing on the heuristics that users used. As discussed, participants used different heuristics to make a decision. Interestingly, these heuristics often resulted in high quality decisions. However, these heuristics still appear to be very cognitively burdensome, so if some features were provided to lower the burden, decision makers might be able to make a better decision more easily.

CHAPTER 7: CONCLUSIONS

Chapter 7 summarizes the results of this dissertation and describes contributions. Following these, the author provides several potential avenues for future work.

7.1 Summary

Can InfoVis techniques help people choose a better nursing home?

Though it appears to be a simple question, answering this required many steps. First, the author reviewed the relevant literature to understand various aspects of nursing home choice. Previous studies showed that selecting a nursing home is often done without consulting the quality information of nursing homes even though such information is publicly available. One of the various reasons discouraging the use of the information is overload caused by the complexity and abundance of quality measures, and the currently available websites, including the NHC website, do not appear to present information properly. In this study, as a solution to the information overload problem, InfoVis techniques were considered. However, numerous InfoVis techniques have been developed, so a subset of techniques was selected using the knowledge of decision science. Adaptive decision behaviors proposed by Payne et al. (Payne, Bettman et al. 1993) particularly inspired the author, so a theoretical framework, called "the VDM framework," was developed to link between InfoVis techniques and various decision strategies, which are often categorized into compensatory strategies and non-compensatory strategies.

Second, an interview study was conducted to better understand how people chose a nursing home. Nineteen participants who had prior experience in choosing a nursing home or anticipated choosing one in the near future were interviewed. Through the interviews, the author could understand how emotionally difficult and complex the decisions are and what kinds of decision factors are important. Other aspects learned from the interviews are as follows: 1) Some participants were skeptical about the validity of information about nursing homes on the Internet, 2) each individual has different circumstances, and 3) people often made a decision under enormous time pressure. These aspects were carefully considered while designing the proposed tool.

Third, based on knowledge gained through literature review and interviews, an InfoVis tool, or VDM, was designed, evaluated, and implemented. Among numerous visualization techniques, ValueCharts was identified the most promising technique since it appeared to support both compensatory and non-compensatory strategies in a balanced manner. Thus, VDM was largely based on ValueCharts. However, some additional features, such as the weighted slider bar and the distribution view, were added to support various cognitive tasks identified by the VDM framework. In other words, the weighting slider bar and the distribution view were expected to support compensatory and non-compensatory decision strategies, respectively.

Fourth, the implementation of VDM was tested via a web-based experiment. The effects of CV and NCV on decision quality were investigated under different amounts of information. Two hundred twenty-two participants completed the surveys and experimental tasks, and 115 participants were identified valid after screening using the tutorial completion ratio, which indirectly indicates whether a participant watched the entire video tutorial or not. The results of analyses of quantitative data showed that the presence of either CV or NCV did not increase decision quality while the smaller number of attributes or the smaller number of alternatives increased decision quality. The participants also perceived VDM with either CV or NCV less usable than the tool without both CV and NCV. However, these results should not mislead one to believe that CV and NCV are without value. The results of analyses of qualitative data and participants' comments showed that some participants found the usefulness and potential of CV or NCV.

Last, an additional interview study was conducted to understand how participants in the web-based experiment learned and used the tool. Eleven participants who belonged to different experimental conditions and had different opinions toward the tool were interviewed. The interview results showed that all of the participants did not rely on CV and NCV to make the final decision. Both CV and NCV turned out to have some usability issues, and interview participants had difficulties understanding how they worked. Instead of using these techniques, participants used various heuristics and decision making strategies, which would provide another interesting direction to enhance VDM.

Altogether, the author unfortunately failed to provide quantitative evidence to support the thesis statement: *In the decision-making scenario of nursing home choice, the quality of decisions made with the assistance of designed InfoVis techniques is better than that made without those techniques present, and the differences between the two groups enlarge as the amount of data considered increases.* However, VDM itself was generally well accepted by participants, and the problems of the proposed visualization techniques were identified. Thus, if an improved version of VDM could resolve some of the identified issues, the author believes that the effectiveness of the InfoVis techniques on decision making would be evident in the near future.

7.2 Contributions

The most direct and tangible outcome of the present study is VDM developed to support the decision making problem of selecting a nursing home. Although the individual visualization techniques (i.e., CV and NCV) were not shown to benefit users to make a critical decision under time pressure, some participants found that these visualization techniques were useful. Thus, further investigation into the utility of these tools is necessary. In addition, the developed tool is currently available to the public at http://nhc.hsi.gatech.edu. Thus, potential decision makers have the opportunity to take advantage of this tool, hopefully resulting in more informed decisions with less effort and time consumption. This benefit is crucial, given the propensity for decision makers to experience not only physical, mental, or emotional stress but also time pressure.

From the perspective of InfoVis researchers and developers, this study provides an example of the employment of user-centered design techniques in the development of VDM with application to a real-world decision making problems. The extensive user interviews in the requirements analysis identified the challenges and needs of real users, and the web-based experiment and follow-up interviews deepened our understanding of how InfoVis techniques can amplify and/or impede human cognitive processes within the context of selecting a nursing home.

Even though this study has been designed to solve a very specific problem, the web-based experiment with 115 participants helped generalize the outcomes of this study. By controlling the presence of InfoVis techniques (i.e., CV and NCV), the effects and interactions of these InfoVis techniques were quantitatively measured. Although the results of the experiment failed to clearly show the benefits of the InfoVis techniques, the results might help other InfoVis researchers who aim to support similar choice procedures. Similar choice procedures can be found throughout healthcare decision making, consumer decision making, managerial decision making, and other domains.

From the perspective of decision science, the results of this study provide decision scientists with an additional set of decision aids, InfoVis techniques. This study provided a tangible example, empirical evidence from a real decision making scenario, and quantitative results of its effectiveness. It is believed that these types of studies can help decision scientists better consider the possibilities and advantages of using InfoVis techniques to support human decision making.

Ultimately, this study represents an initial effort to combine the two disparate fields of decision making and InfoVis. The proposed VDM framework provides a theoretical link between these two fields, so other practitioners and researchers who are interested in using InfoVis techniques to support decision makers can identify which InfoVis techniques are more promising for a given decision making context. In addition, the results of the web-based experiment and follow-up interviews provide empirical evidence of how InfoVis techniques could affect decision behavior. Even though the context of this study is limited to nursing home choice, the results of this study could be generalized to other areas.

7.3 Future Research

Even though the present study provided some insights about the effects of information visualization in supporting nursing home choice, it failed to provide empirical evidence showing that proposed visualization techniques actually improve decision quality. Since the analyses of qualitative results revealed that the proposed

InfoVis techniques have potential, a lack of quantitative evidence does not necessarily imply that the entire InfoVis techniques are inappropriate to enhance decisions. Instead, the author identified the following areas of improvement to clarify the benefits of InfoVis techniques in the context of decision making.

The first area would be enhancing the usability of the proposed InfoVis techniques, so that decision makers can use the tool without having a steep learning curve. Several usability issues have been discussed: difficult concepts and terminologies, hidden algorithms to calculate the summation score, and hidden information while zoomed-out. To resolve these issues, the current visualization techniques could be updated as follows: 1) The distribution view can be renamed to "rankings," "category ranking," or "category ranking view;" 2) while the zoomed-out view is used, the fisheye view can be used to show the detailed information of the selected/hovered nursing home; 3) the stacked histogram view can be used to show how all of the values contribute to the summation score; and 4) additional instruction can be added to clarify that the smaller values are better.

Another area of improvement would be providing other visualization techniques to support decision strategies observed during the follow-up interviews. As discussed earlier, various decision strategies other than WADD and EBA were observed. To support these decision strategies, additional visualization techniques could be developed. However, a single tool cannot support every possible decision strategy because it would make the tool too complex. Thus, the future study should either investigate what is the most commonly used decision strategy or design a way to guide users to use a certain decision strategy or strategies. These new strategies should be in line with the mental models of the target population.

Another direction that might be fruitful would be applying VDM to other decision making contexts. In the context of nursing home choice, participants became extremely risk-adverse since it is not a trivial decision. This attitude might prevent participants from using a new technique to make a decision. If it is used in other contexts of casual decision making and if the target population is more computer-savvy, unfamiliar user interfaces could be more accepted and the effectiveness of the proposed tool may be clearer.

Future research also could move beyond visualization of numerical information. Numerical information is more comparable and objective, so visualizing it has been a focus of this dissertation project. However, much non-numerical information exists in the world, and collecting and utilizing it presents its own set of challenges. If a method to deal with non-numerical information in decision contexts is found, it will have various application areas.

APPENDIX A

Table 49. Numbers of nursing homes registered in the NHC website

Territories/States	Count	Territories/States	Count
California	1284	Mississippi	203
Texas	1140	South Carolina	177
Ohio	964	Oregon	139
Illinois	802	Arizona	134
Pennsylvania	717	West Virginia	131
Florida	681	Maine	113
New York	657	South Dakota	111
Missouri	517	Montana	97
Indiana	515	Utah	93
Massachusetts	456	Rhode Island	90
Iowa	455	North Dakota	83
Michigan	427	New Hampshire	82
North Carolina	421	Idaho	80
Minnesota	398	New Mexico	73
Wisconsin	398	Hawaii	47
New Jersey	362	Nevada	47
Georgia	359	Delaware	44
Kansas	352	Vermont	41
Oklahoma	343	Wyoming	39
Tennessee	326	District of Columbia	20
Louisiana	294	Alaska	15
Kentucky	292	Puerto Rico	7
Virginia	278	Guam	1
Washington	246	Virgin Islands of the U.S.	1
Connecticut	245	American Samoa	0
Arkansas	237	Federated States of Micronesia	0
Maryland	233	Marshall Islands	0
Alabama	229	Northern Mariana Islands	0
Nebraska	226	Palau	0
Colorado	212	U.S. Minor Outlying Islands	0
Total: 15934 nursing homes			

Ordered by the number of nursing homes for each territory or state. The data were collected on September 3, 2006.

APPENDIX B

Table 50. Taxonomy of biases in decision making (adapted from Arnott 2006)

Category	Name	Description	References
Memory biases	Hindsight	In retrospect, the degree to which an event could have been predicted is often overestimated	(Fischhoff 1982; Mazursky and Ofir 1997)
	Imaginability	An event may be judged more probable if it can be easily imagined	(Tversky and Kahneman 1974; Taylor and Thompson 1982)
	Recall	An event or class may appear more numerous or frequent if its instances are more easily recalled than	(Tversky and Kahneman 1981; Taylor and Thompson 1982)
	Search	An event may seem more frequent because of the effectiveness of the search strategy	(Tversky and Kahneman 1974; Bazerman 2002)
	Similarity	The likelihood of an event occurring may be judged by the degree of similarity with the class it is perceived to belong to	(Horton and Mills 1984; Joram and Read 1996)
	Testimony	The inability to recall details of an event may lead to seemingly logical reconstructions that may be inaccurate	(Wells and Loftus 1984; Ricchiute 1997)
Statistical biases	Base rate	Base rate data tends to be ignored when other data are available	(Fischhoff and Beyth-Marom 1983; Bar-Hillel 1990)
	Chance	A sequence of random events can be mistaken for an essential characteristic of a process	(Wagenaar 1988; Ayton, Hunt et al. 1989)
	Conjunction	Probability is often overestimated in compound conjunctive problems	(Bar-Hillel 1973; Teigen, Martinussen et al. 1996)
	Correlation	The probability of two events occurring together can be overestimated if they have co-occurred in the past	(Tversky and Kahneman 1973; Alloy and Tabachnik 1984)
	Disjunction	Probability is often underestimated in compound disjunctive problems	(Bar-Hillel 1973; Bazerman 2002)
	Sample	The size of a sample is often ignored in judging its predictive power	(Nisbett, Krantz et al. 1983; Sedlmeier and Gigerenzer 1997)
	Subset	A conjunction or subset is often judged more probable than its set	(Thuring and Jungermann 1990; Briggs and Krantz 1992)

Table 50 (continued).

Confidence biases	Completeness	The perception of an apparently complete or logical data presentation can stop the search for omissions	(Fischhoff, Slovic et al. 1978; Hogarth 1987)
	Control	A poor decision may lead to a good outcome, inducing a false feeling of control over the judgment situation	(Greenberg 1996; Hastie and Dawes 2001)
	Confirmation	Often decision-makers seek confirmatory evidence and do not search for disconfirming information	(Heath 1996; Russo, Medvec et al. 1996)
	Desire	The probability of desired outcomes may be inaccurately assessed as being greater	(Olsen 1997; Hastie and Dawes 2001)
	Overconfidence	The ability to solve difficult or novel problems is often overestimated	(Brenner, Koehler et al. 1996; Keren 1997)
	Redundancy	The more redundant and voluminous the data, the more confidence may be expressed in its accuracy and importance	(Remus and Kottemann 1986; Arkes, Hackett et al. 1989)
	Selectivity	Expectation of the nature of an event can bias what information is thought to be relevant	(Kahneman and Tversky 1973; Schwenk 1988)
	Success	Often failure is associated with poor luck, and success with the abilities of the decision-maker	(Miller 1976; Hogarth 1987)
	Test	Some aspects and outcomes of choice cannot be tested, leading to unrealistic confidence in judgment	(Einhorn 1980; Christensen-Szalanski and Bushyhead 1981)
Adjustment biases	Anchoring and adjustment	Adjustments from an initial position are usually insufficient	(Chapman and Johnson 1994; Ganzach 1996)
	Conservatism	Often estimates are not revised appropriately on the receipt of significant new data	(Fischhoff and Beyth-Marom 1983; Nelson 1996)
	Reference	The establishment of a reference point or anchor can be a random or distorted act	(Tversky and Kahneman 1974; Bazerman 2002)
	Regression	That events will tend to regress towards the mean on subsequent trials is often not allowed for in judgment	(Kahneman and Tversky 1973; Joyce and Biddle 1981)

Table 50 (continued).

Presentation biases	Framing	Events framed as either losses or gains may be evaluated differently	(Kahneman and Tversky 1979; Kunberger 1997)
	Linear	Decision-makers are often unable to extrapolate a nonlinear growth process	(Wagenaar and Timmers 1979; Mackinnon and Wearing 1991)
	Mode	The mode and mixture of presentation can influence the perceived value of data	(Saunders and Jones 1990; Dusenbury and Fennma 1996)
	Order	The first or last item presented may be over-weighted in judgment	(Yates and Curley 1986; Chapman, Bergus et al. 1996)
	Scale	The perceived variability of data can be affected by the scale of the data	(Remus 1984; Ricketts 1990)
Situation biases	Attenuation	A decision making situation can be simplified by ignoring or significantly discounting the level of uncertainty	(Beer 1981; Hogarth 1987)
	Complexity	Time pressure, information overload and other environmental factors can increase the perceived complexity of a task	(Maule and Edland 1997; Ordonez and Benson 1997)
	Escalation	Often decision-makers commit to follow or escalate a previous unsatisfactory course of action	(Northcraft and Wolf 1984; Drummond 1994)
	Habit	An alternative may be chosen only because it was used before	(Slovic 1975; Hogarth 1987)
	Inconsistency	Often a consistent judgment strategy is not applied to an identical repetitive set of cases	(Showers and Charkrin 1981; Moskowitz and Sarin 1983)
	Rule	The wrong decision rule may be used	(Sage 1981; Goodwin and Wright 1991)

APPENDIX C

Interview Questionnaire Used for Requirements Analysis

1. How did you select the nursing home you chose? Please describe it step by step if possible.
2. What were the biggest difficulties in making the decision?
3. Which step was most difficult?
4. What were the most important factors in making this decision?
5. How did you utilize the information sources you indicated on the survey?
6. Did you feel that you had sufficient information to make the decision?
7. If not, why do you feel that way?
8. Did you rely on the Internet to make your decision?
9. If you used the Internet, was it helpful?
10. If you remember some of helpful Web sites, can you let me know the addresses?
11. Do you have any specific reasons why you couldn't use the Internet as an information source?
12. Have you ever visited the Nursing Home Compare Web site?
13. Did you use it to make your final decision?
14. How helpful was it?
15. What would you change about this Web site?
16. Would you try to choose two best nursing homes in your area using this Web site?
17. Do you think this Web site would be helpful to you in selecting a nursing home?
18. What would you change about this Web site?
19. Is there anything I haven't asked you that you think is important or worth discussing?

APPENDIX D

The Script for Video Tutorials

Your goal in this experiment is to find the best nursing home for Jane's father, who just had a hip fracture.

While choosing a nursing home for him, you have to consider many attributes and many nursing homes. This can be a difficult task, so we will provide you with a tool.

The tool is essentially a table. Each column represents an attribute, such as percentage of residents who experience pressure sores, while each row represents a different option or nursing home.

The value in each cell is represented by both a bar graph and a number. Since this value represents some sort of risk, such as percentage of residents who experience significant pain, the shorter bar graph is, the safer the nursing home is.

When you hover your mouse cursor over the header of each column, you will see a detailed description of the attribute in the top yellow box.

If you click on the header of the column where the attribute label is, you can sort the column as you do in spreadsheet software, such as Microsoft Excel.

[This paragraph is only shown and narrated to the participants who experienced CV techniques] Some attributes of a nursing home are more important than others for Jane’s father. You can change the importance rating for each attribute by moving the slider bar. When interacting with the importance control, you can see that the width of the corresponding column change as well. At the same time, a special column, called the "SUM" Column, updates its values. The SUM column contains the weighted summary of all columns. So, if the value of the SUM column is small, it means that the overall risk of the nursing home is small. Of course, the values of the SUM column depend on the weights and values of the different attributes.

On the left side, you can see the zoom in and out radio buttons. If you zoom out, the bar graphs shrink vertically and the numbers are hidden, so that you can see all the rows or nursing home choices in one screen. If you want to see the details for a given nursing home or subset of nursing homes, select the "zoom in" radio button.

[This paragraph is only shown and narrated to the participants who experienced NCV techniques.] Another feature is the "Distribution" view. To demonstrate this feature, let’s take a look at NH01. This nursing home has values of 12%, 3%, 19%, and 0% for the attributes. It sounds like it might be a good choice, but you don't know how it compares with the other nursing homes. Then, if you select the NH01 and press the Distribution radio button, every column is sorted at the same time. You should note that when the Distribution view is selected, the attribute values for a nursing home are no longer consolidated in the same row. The values of NH01’s attributes are now highlighted to illustrate where they fall within the distribution of values for a given attribute. Now you can see that 12%, 3%, and 0% are actually better than other nursing homes. However, 19% of HPS or pressure sores seems worse than other nursing homes.

NH05 seems to have a good overall rating. Select NH05 and press the "Choose Selected" button, and your choice has been made.

APPENDIX E

Figure 24. A screen shot of the experimental website - the introduction page

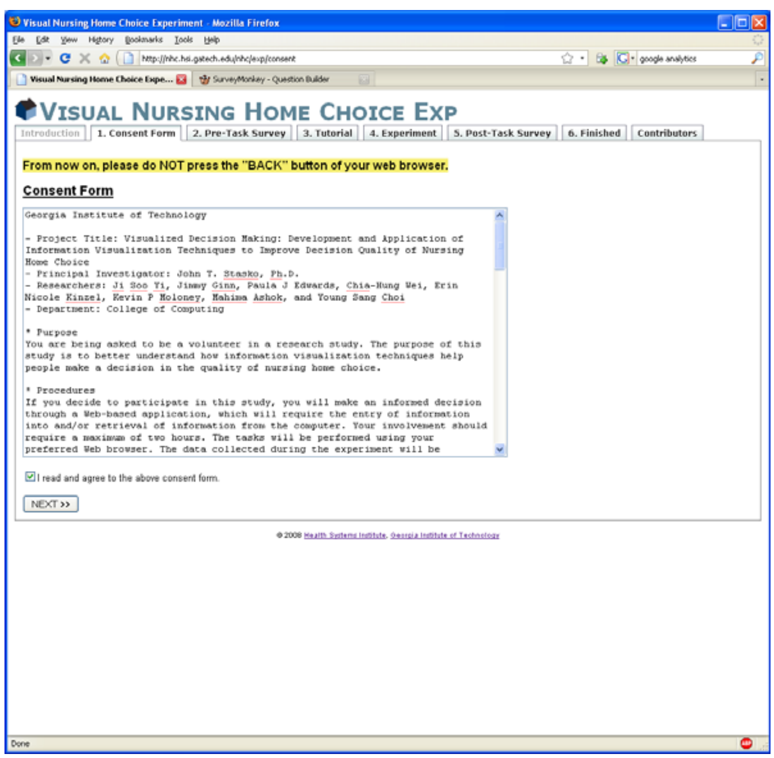

Figure 25. A screen shot of the experimental website - the consent form page

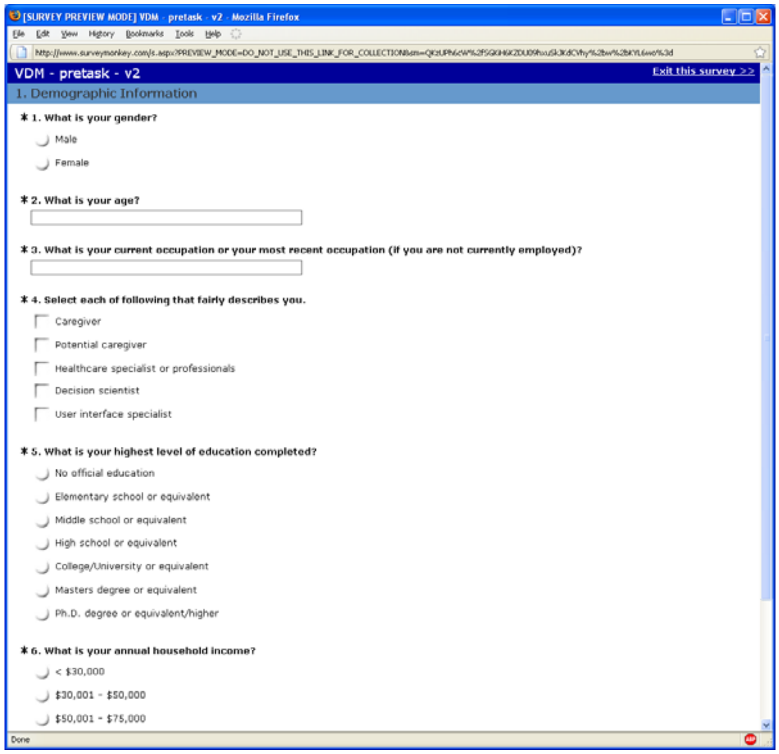

Figure 26. A screen shot of the experimental website - the pre-task survey page

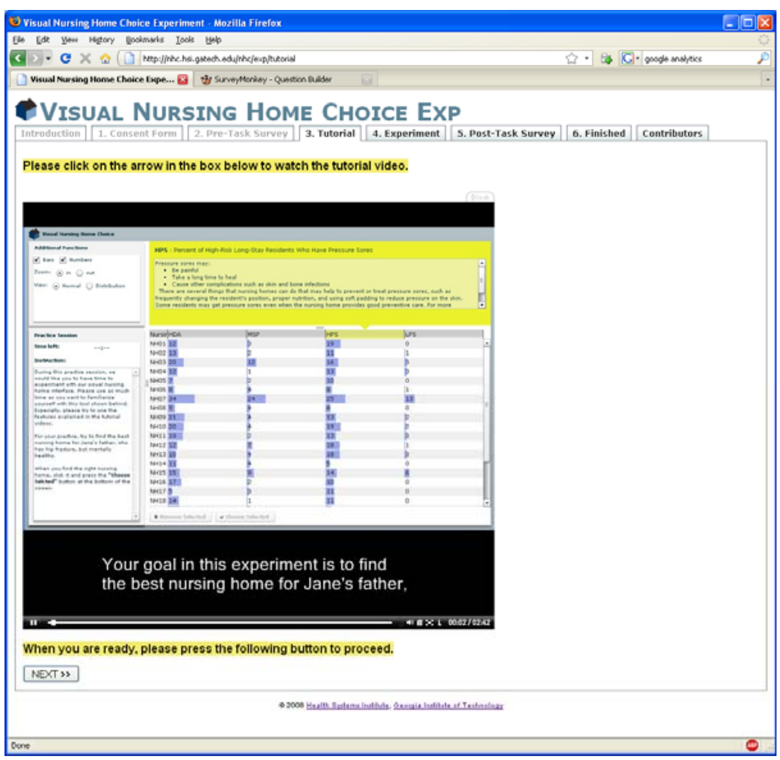

Figure 27. A screen shot of the experimental website - the tutorial page

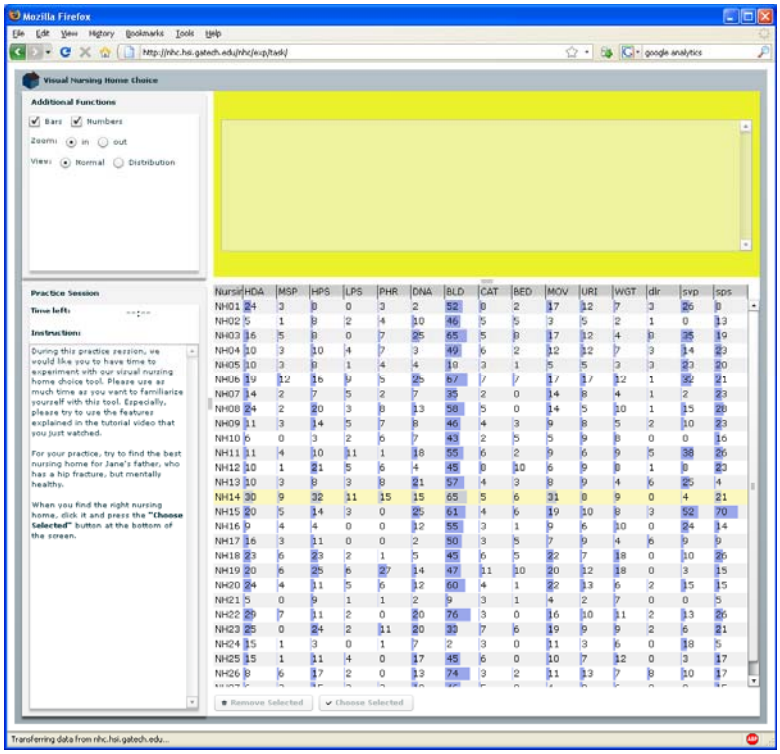

Figure 28. A screen shot of the experimental website - the task page

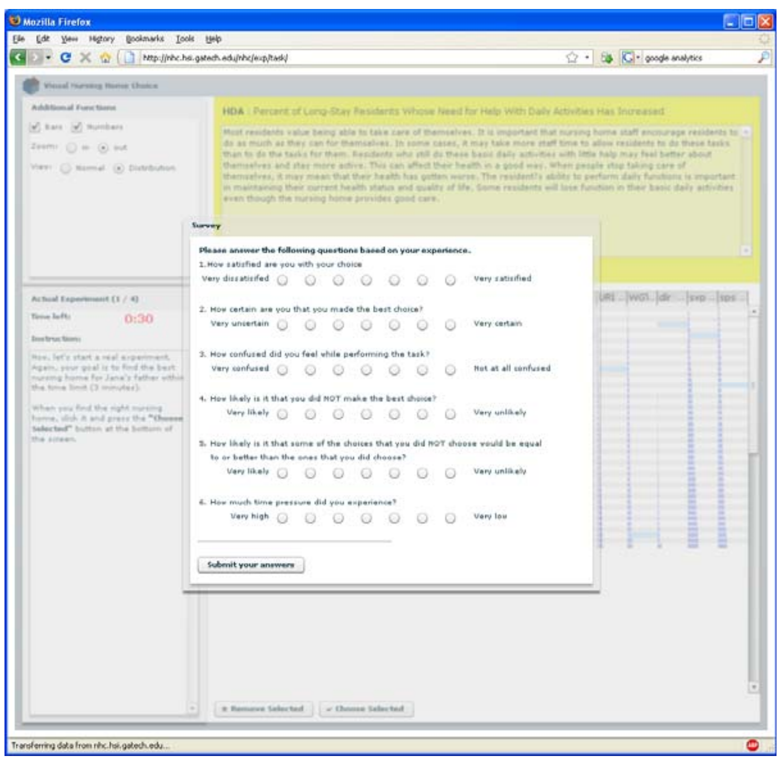

Figure 29. A screen shot of the experimental website - the post-trial survey

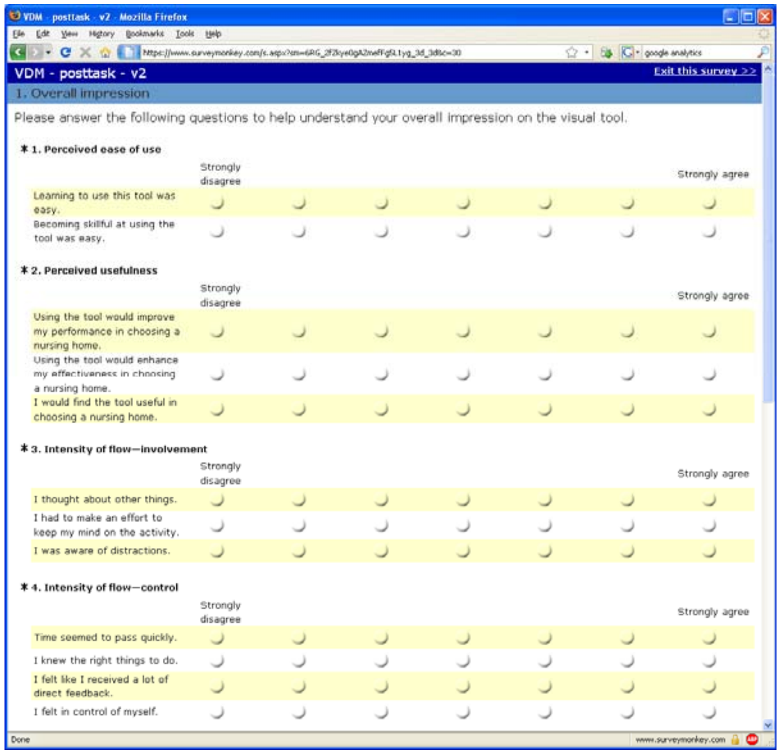

Figure 30. A screen shot of the experimental website - the post-task survey

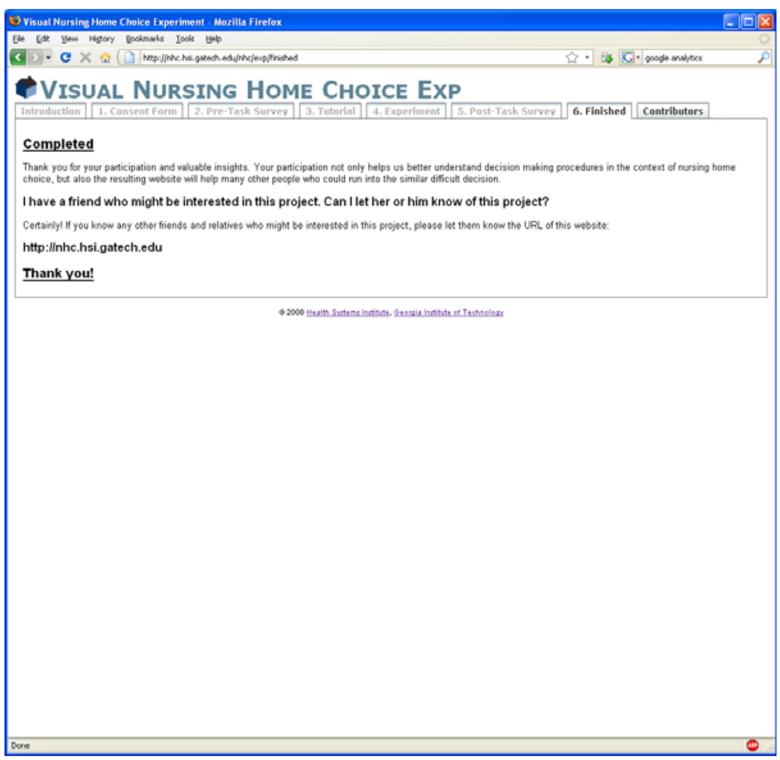

Figure 31. A screen shot of the experimental website - the finished page

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